CRANFIELD UNIVERSITY

NARJESS TEYSSIER

HOW THE CONSUMER CONFIDENCE INDEX COULD INCREASE AIR TRAVEL DEMAND FORECAST ACCURACY?

SCHOOL OF ENGINEERING

AIR TRANSPORT GROUP

PhD THESIS

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April 2004 – September 2012

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September 2012

This thesis is submitted in (100%) fulfilment of the requirements for the PhD

ABSTRACT

Because of the complex nature of the air transportation industry with continuous changes in the environment, the past records of air traffic forecasters, either using trend extrapolation or causal models or even more sophisticated methods have not produced accurate results. In recent years, the trend has been to develop air travel demand forecasts based on econometric equations, which specify a relationship between passenger traffic and a number of traditional key economic variables. However these forecasts do not take into account air traffic downturns or strong increases.

Periods of economic or political uncertainty are associated with consumer confidence volatility, suggesting that swings in confidence could influence air travel demand.

The failure of forecasters to predict the repeated peaks and troughs since 2001 has renewed interest in supplementing econometric forecasts with qualitative indicators such as consumer confidence indices. These variables are available for some countries and the aim of this research is to find whether forecasts based on these indices are more accurate in predicting short-term traffic up and downs.

Through the analysis of three case studies, this thesis examines how the introduction of a confidence index in the air travel demand model, including only macroeconomic variables, could have some ability to improve the forecast accuracy of the model. For each case study, the demand for the market has been divided according to the existing supply side segments, namely legacy carriers, low cost carriers and non-scheduled airlines.

The results show that this confidence index has some ability to improve the forecast accuracy of both, the global top-down and the bottom-up models built for some supply side segments, notably the legacy ones during periods of uncertainty such as 1991, 2001, 2008 and 2009. The results are also suggesting that the forecasting power of this index is increasing when applied to more mature markets such as the demand linked to the US legacy carriers or to the European charter airlines.

This study is appraising the performance of consumer confidence indexes by examining their impact on different air travel demand forecasts.

ACKNOWLEDGEMENTS

I would like to thank Airbus for funding part of this PhD programme, and more especially Mr Adam Brown, the former Vice-President of the Airbus Marketing department, who was fully convinced by the usefulness of this research and has strongly encouraged me to pursue my efforts in this direction.

My sincere gratitude and thanks are extended to Pr Fariba Alamdari, Dr Peter Morrell and Dr Zheng Lei, for their guidance and encouragement as well as for their support in understanding my particular situation.

During my PhD I have enjoyed both my subject matter and all the precious knowledge that I have been able to acquire during these last years. I am sure that they will be quite helpful for improving the inputs I am producing in my current and future professional adventures.

Finally I take this opportunity to thank all my family members for their help and patience during these last months, especially my mother Wassila Toujani.

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NOTATION

AAGR : Average Annual Growth Rate

ABC: Advanced Booking Charter

ACCC: Australian Competition and Consumer Commission

ACI: Airports Council International

ADA: Airline Deregulation Act

ADF: Augmented Dickey Fuller

AEA : Association of European Airlines

A4A: Airlines For America

AIC: Akaike's Information Criterion

AIH: Absolute Income Hypothesis

APC: Average Propensity to Consume

ARMA: Auto Regressive Moving Average

ARIMA: Auto Regressive Integrated Moving Average

ASA: Air Service Agreement

ASK: Available Seat Kilometre

ATA: Air Transport Association

ATI: Anti-Trust Immunity

BA: British Airways

BCAC: Boeing Commercial Airplane Company

BIC: Bayesian information criterion

BJ: Box-Jenkins

B.L.U.E.:	Best Linear Unbiased Estimator
BLS:	Bureau of Labor Statistics
BRIC:	Brazil, Russia, India and China
BTCE:	Bureau of Transport and Communication Economics (**Australia**)
BTR:	Bureau of Tourism Research (Australia)
BTS:	Bureau of Transportation Statistics
CAA:	Civil Aviation Authority
CCI:	Consumer Confidence Index
CMO :	Current Market Outlook
CPI:	Consumer Price Index
CRS:	Computer Reservation System
CSI:	Consumer Sentiment Index
DFFITS:	DiFerence in FITted valueS
DoT :	Department of Transportation (**United States**)
DW:	Durbin Watson
EC:	European Community
EC:	European Commission
ECAA:	European Common Aviation Area
ECM:	Error Correction Mechanism
EEA:	European Economic Area
EIA:	Energy Information Administration (US)
ENAC:	Ecole Nationale de l´Aviation Civile

ERAA :	European Regions Airlines Association
EU:	European Union
FAA :	Federal Aviation Administration
FFP:	Frequent Flyer Programme
FTK:	Freight Tonne Kilometre
GAAP:	Generally Accepted Accounting Principles
GATO:	Global Air Transport Outlook (ICAO)
GCD:	Great Circle Distance
GDP:	Gross Domestic Product
GfK:	Gesellschaft für Konsum
GMF:	Global Market Forecast
GNP:	Gross National Product
IATA:	International Air Transport Association
ICAO:	International Civil Aviation Organisation
IFRS:	International Financial Reporting Standards
INSEE:	Institut National de la Statistique et des Etudes Économiques
ISAE:	Institute of Studies and Economic Analysis
ITA:	Institut du Transport Aérien
JV:	Joint Venture
LCC:	Low Cost Carrier
LCH :	Life Cycle Hypothesis
LH:	Lufthansa

Ln or Log:	Napierian Logarithm
MFE:	Mean Forecast Error
MPC:	Marginal Propensity to Consume
MSE:	Mean Square Error
NINJA:	No Income No Job No Asset
NWA:	Northwest Airline
OAA:	Open Aviation Area
OAG:	Official Airline Guide
OD:	Origin/Destination
OEM:	Original Equipment Manufacturer
OFOD:	On Flight Origin Destination
OLS:	Ordinary Least Square
OSA:	Open Skies Agreement
P.A.:	Per Annum
PIH:	Permanent Income Hypothesis
PMI:	Purchasing Managers buying Intentions
PPP:	Purchasing Power Parity
RESET:	(Ramsey) Regression Equation Specification Error Test
RITA:	Research and Innovative Technology Administration
RMSE or:	Root Mean Square Error
RMSD:	Root Mean Square Deviation
RMSFE:	Root Mean Square Forecast Error

RPK:	Revenue Passenger Kilometer
RPM:	Revenue Passenger Mile
RSS:	Residual Sum of Squares
RU:	Rate of Unemployment
SARS:	Severe Acute Respiratory Syndrome
SAS:	Statistical Analysis Software
SBC:	Schwarz's Bayesian Criterion
SBIC:	Schwarz's Bayesian Information Criterion
SSE:	Sum of Square Error
TFS:	Traffic by Flight Stage
UAL:	United Airlines
UK:	United Kingdom
UN:	United Nations
US:	United States of America
VFR:	Visiting Friends and Relatives
VIF:	Variance Inflation Factor
WTC:	World Trade Center
WTI:	World Texas Intermediate

1. INTRODUCTION

The air transport industry is a value chain, where all the stakeholders from airlines, airports, air navigation service providers, regulators, aircraft manufacturers and the others are playing a determinant role. However the necessary to maintain a virtuous chain is played either by the passenger or the piece of freight to be carried. Therefore for each stakeholder it is vital to quantify and project air travel demand in order to take the right decisions to quantify demand in a future time period. Quantification can be made in terms of passenger enplanements, traffic, freight tons, number of aircraft to purchase or to produce, as planning cannot be made without forecasting demand. In addition to planning, forecasting is useful for analysis and control purposes.

Forecasting air travel demand is the indispensable step for any other projected demand related to the value chain of air transport, should it be fleet planning, future requirements of licensed personnel and training capacities, infrastructure building or aircraft production.

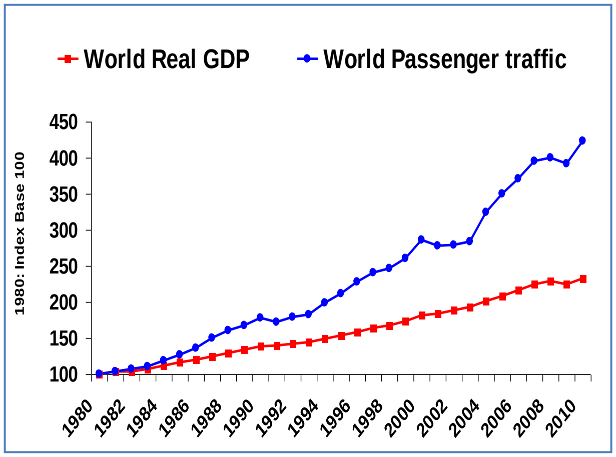
Aircraft manufacturers are predicting long-term average traffic growths which are the basis to develop the forecast of open demand for the world aircraft fleet and to plan their production pace in view of their delivery schedule. Therefore traffic forecast accuracy is important for their short-term vision, to support decisions for budgeting, reporting, planning production, scheduling their purchases, monitoring their sales, specifying the next generation of airliners as well as building strategies. This is why a little improvement in accurately forecast air travel demand can easily translate into substantial gains in profits, as well as limiting losses, especially during crisis times.

1.1 Research background

A range of factors affect air travel demand and each factor can stimulate or constrain air travel growth (Abed et al, 2001). Core demand for air travel is assumed to be supported by the economic and demographic conditions in the origin and destination communities (Bhadra and Kee, 2008). Air travel demand is influenced by macro-economic determinants and Tam et al (2003) identified key relationships between the economy and the air transportation system. In the past thirty years, although growth in world air travel has been greater than world economic growth, analytical studies, such as the one conducted by Ishutkina (2009) at the world level, showing that the economy drives the demand for air transportation services, indicate that there is a high correlation between the economic growth and air traffic respectively measured in Gross Domestic Product (GDP) and Revenue Passenger Kilometres (RPKs). The rate of growth of air travel seems to follow the developments in the world's GDP (Doganis, 2001), as air traffic growth rates show a high degree of cyclicality which is correlated with economic growth cycles measured by the GDP (Hätty and Hollmeier, 2003).

As an example of this growth, shown in Figure 1, the output of the air transport industry, the world passenger traffic, measured in terms of RPKs, has increased by a factor of around 4 between1980 and 2010, while total GDP which is the broadest available measure of world economic output, increased by a factor of about 2 over the same period. The world passenger traffic represents the total (international and domestic) scheduled and non-scheduled passenger traffic carried by the air carriers domiciled[1] in a country.

Figure 1: Air traffic growth has outpaced economic growth



Source: ICAO, IHS / Global Insight

Air traffic growth in excess, or below of GDP growth is usually explained by other factors, as notably, travel decisions are now increasingly based primarily on the availability of tickets at an affordable price (Brown, 2003)[2]. Determinants such as population and income distribution (Vedantham and Oppenheimer, 1998) are also playing an increasing role in the way of forecasting future traffic patterns in certain markets, while travel behaviour, including travel time budgets and travel costs (Schafer, 2000) are more significant in others.

As stated by Swan (2008), the most common forecast for air travel involves regressing travel against economic activity such as GDP. The GDP for the origin and destination are often summed, and the metric for air travel is usually RPKs. He pointed out the problems linked with this approach, as for him, the traditional formula determining traffic forecast through GDP growth and fares reduction is not precise enough to determine the near term fluctuations.

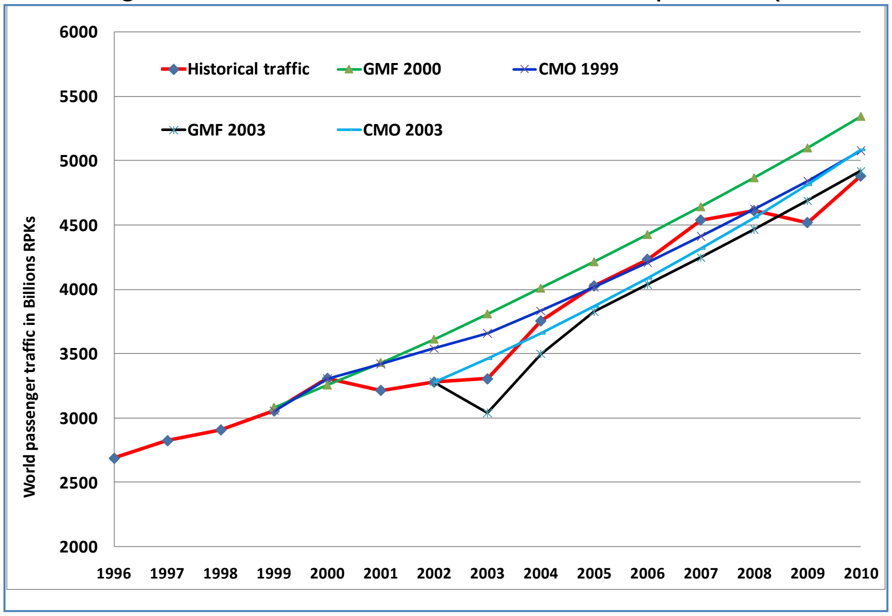
Indeed it can only give a trend as it is not possible to separate the GDP growth pattern (population or wealth level growth), and yield is a too average measure of the different ticket fares. When looking at the last six years, GDP

[1] The Country in which the air carrier has its principal place of business.

[2] As mentioned in the 2003 Airbus Global Market Forecast (GMF)

explanatory power has severely declined, showing a decrease in the goodness of the fit (Figure 2), even with an extensive use of dummy variables[3].

Figure 2: Forecasting world air travel demand in different periods (before 2004)



Source: Airbus GMF(Global Market Forecast) and Boeing CMO (Current Market Outlook)

The great majority of the methodologies used by aircraft manufacturers to forecast air traffic is based on econometric models that are by far the most frequently used method for forecasting aviation demand (Wensveen, 2007).

The failure of air traffic forecasters to predict in a timely manner the persistent air transport slowdown (especially in the US), and then the strong air traffic growth registered in 2004, 2005, 2006 and 2007, has renewed interest in the idea of supplementing model-based forecasts with information from other more qualitative indicators: the Consumer Confidence Index is one of these variables. Traffic in the short-term responds to consumer confidence (Swan, 2005) and consumer confidence moves when GDP moves are large, while large GDP moves show large traffic responses. The forecasting power of the Consumer Confidence Index regarding air travel demand modelling and projections is assessed in this thesis.

1.2 Research aim and objectives

Most forecasts of aviation demand are based on the premise that air transport demand is determined primarily by economic development. It is established that transport is closely related to economic activity (Profillidis, 2004), and more specifically, air travel demand is strongly determined by income

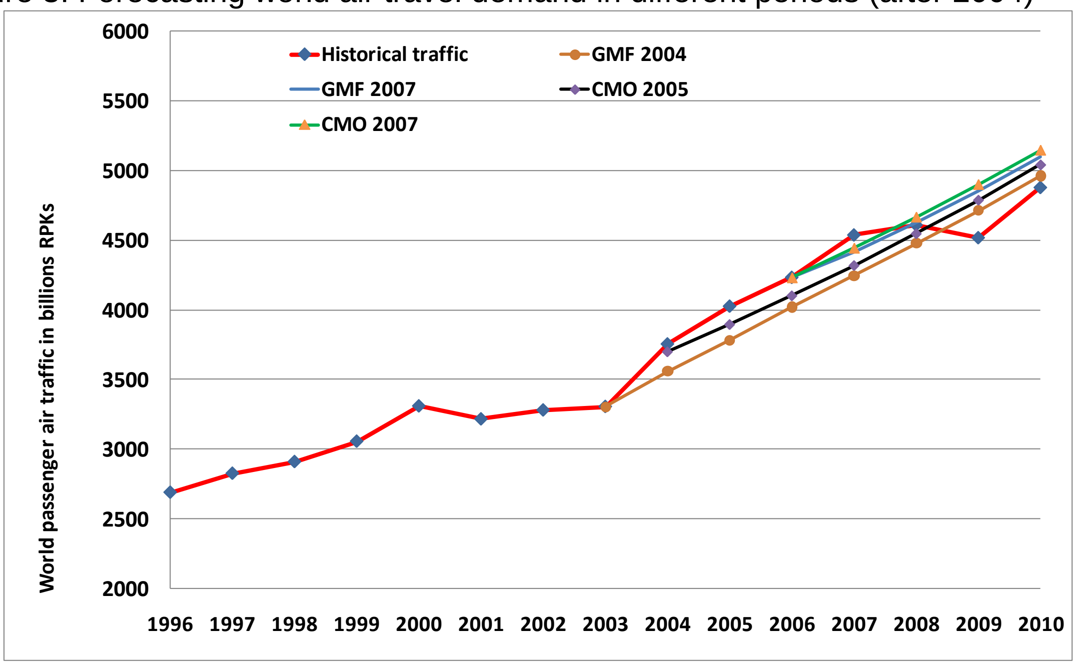
[3] The dummy captures the degree of abnormal behaviour in a crisis period compared to a normal one

(personal income) in the case of pleasure travel (Garvett and Taneja, 1974) and Gross National Product (GNP**)** in the case of business travel. It is noteworthy that GDP and GNP are closely related as both measure the size and strength of the economy. There are different ways to calculate GNP, but in the expenditure approach to calculate GNP, it is expressed as a sum of GDP and Net Income Receipts (Net income from assets abroad).

1.2.1 Research background

According to Wensveen (2007), causal models are unquestionably the most sophisticated type of forecasting method used today, as well as the most frequently used in air travel demand. Although causal models are used quite extensively by regulatory authorities such as the Federal Aviation Administration (FAA), international organizations such as Airports Council International (ACI) and other industry sources, such as Boeing , Rolls Royce, Bombardier or Airbus, it is important to recognize their limitations and this will be discussed more in detail in Chapter4.

Figure 3: Forecasting world air travel demand in different periods (after 2004)



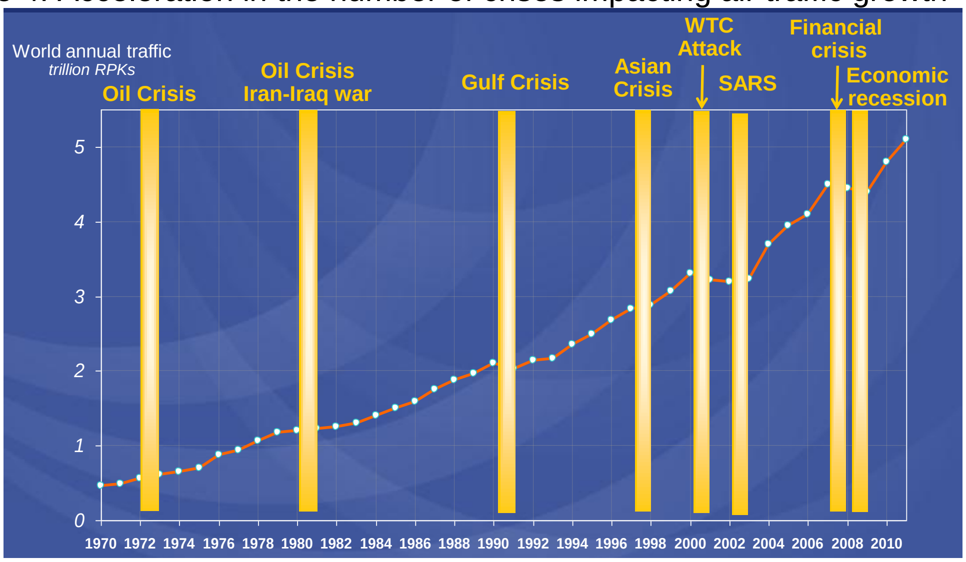
Source: Airbus GMF (Global Market Forecast),Boeing CMO (Current Market Outlook)

As shown in Figures 2 and 3, for the world air travel markets since 2000 the issued forecast (estimations from aircraft manufacturers' forecasts) are far from the historical pattern: 2000, 2001 and 2002 models are unable to catch the crisis effect; while 2003 and 2004 models could not capture the size of the recovery effect showing a return to the initial trend forecasted in 2000. The same phenomenon has occurred for the forecasts issued in 2006 and 2007.

Besides, forecast accuracy in the short term is subject to factors or external shocks that no econometric model could accommodate, such as wars, terrorist action or a high fuel price.

Globalization of our current world has accelerated the rhythm and the occurrences of the crises, should it be economical, political, climatic, health or security related ones, as shown here below in Figure 4.

Figure 4: Acceleration in the number of crises impacting air traffic growth



Source: ICAO

The crisis path is accelerating as in thirty years, between 1970 and 2000, air travel has faced four major external shocks (1973 and 1979 oil crises, 1980 the beginning of the Iran-Iraq war, 1991 gulf crisis and 1997 Asian economic crisis), while between 2000 and 2010, the air transport industry has been under attack by no less than four shocks, namely the 2001 World Trade Center (WTC) attack (known as 9/11), 2003 Severe Acute Respiratory Syndrome **(**SARS), the 2008 financial crisis and the 2009 economic recession.

Leading economic indicators have been widely employed in the economic literature for the purpose of forecasting business activities. The usefulness of leading indicators is that it enables researchers to determine and predict turning points in the cyclical movements of an activity of interest (Jones and Chu Te, 1995). In the literature, it is well acknowledged that income and air fares are the leading demand determinants in air travel demand analyses. According to the literature review conducted by an Intervistas study in 2007 for the International Air Transport Association (IATA), out of 23 published papers, many of them included an income variable , while all of them found that there was a significant demand response to changes in air fares, such that increases in air fare lead to lower passenger traffic demand.

In addition, other leading indicators have been considered in the literature, such as assets (Alperovich and Machnes, 1994) and Consumer price index (CPI), or exchange rate (Hamal, 1998).

However, there are several indicators which already exist in the economic literature but are largely neglected in air travel demand research, notably consumers' expectations of the future economy. Future actions of consumers can be anticipated by surveying the consumer outlook on the economy in order to determine future consumption habits. The University of Michigan's Consumer Sentiment Index (CSI) was devised in the fifties by Katona in order to track consumer sentiment in the economy of the United States (US).

A vast amount of academic research on consumer sentiment indexes has arrived at the conclusion that they do marginally aid in predicting consumer expenditure in the near term. Bram and Ludvigson (1998) for example found that the two confidence indexes in the US provide statistically significant explanatory power of consumer spending two to four quarters ahead. Easaw et al. (2005) arrived at a similar conclusion in their analysis of consumer sentiment indexes and consumption in the United Kingdom (UK).

In contrast, Throop (1992) found that changes in sentiment caused changes in consumption expenditures. When he replaced the Consumer Sentiment Index (CSI) with economic variables that he found predicted sentiment, namely unemployment and inflation, forecast errors were usually lower than in regressions where the CSI was used. However, over the period of the Gulf War, consumption forecasts were more accurate if the CSI was used. Throop concluded that sentiment ordinarily has little complementary value in forecasting consumption, but when an unusual event occurs the CSI is likely to improve forecasts.

In a study dedicated to tourism demand, Allen and Yap (2009) found that although the income and tourism price variables are still the important determinants of Australian domestic tourism demand, other variables such as consumer sentiment index (to a certain extent), can play an important role in influencing Australians' decisions to travel domestically.

In the Boeing CMO (Current Market Outlook) 2010, it is reported that consumer confidence and business profits can be of strong influences on air travel demand during a business cycle, while, according to the Henry Fund Research[4] (2005), since consumer spending affects leisure travel as well as economic activity, the consumer confidence index is an interesting leading indicator for the airline industry.

In view of the above, this thesis intends to examine whether the consumer confidence indicators (apart from income and price variables) can influence air travel demand.

[4] The Henry Fund is an endowed equity portfolio managed by select MBA students enrolled in the Applied Securities Management course at the Henry B. Tippie School of Management. The fund invests in companies that are industry leaders with above-average investment opportunities.

1.2.2 Research objectives

More specifically, and based on Garner (1991) and Throop (1992) research finding that consumer confidence indices are useful to forecast aggregate consumption in periods of major shocks, the forecasting value of these indices will be tested for modeling air transport consumption during crisis times.
The specific objectives of this research are the following:

- To examine if the consumer confidence indicator has an intrinsic forecasting power for evaluating air travel demand
- To assess if during crisis time or in normal context, this indicator improves forecast accuracy when added to other socio-economic variables in the modelling equation
- To analyse if this indicator has more explanatory power when modelling air travel demand for the segment carried by the Low Cost Carriers (LCCs) or the network carriers or even the non-scheduled airlines (when applicable)
- To identify issues and constraints linked to the use of this indicator in forecasting air travel demand
- To provide other potential research direction with regard to air transport modelling in other markets

The forecasting power of the Consumer Confidence Index will be tested first for the Domestic US air travel market, as it is the world most important market, in terms of RPKs' market share, but also because it has been the most affected by the various crises. Then the methodology will be applied to another liberalized market, the second largest one, the European air travel market, as in the European Union (EU) context, it can be compared to the US Domestic one. Finally, the third test will be applied to an international market, the third largest one in the world, the EU-US air travel market.

1.3 Research questions and thesis layout

1.3.1 Research questions

In order to fulfill the main objectives of this research, the following questions are addressed in this thesis through the analysis of three case studies:

a) How has the US domestic air transport market been developed since it has been deregulated?
b) What are the main features and characteristics of this market?
c) How consumer confidence can improve the models built for estimating air travel demand for this market?
d) Does consumer confidence has different impacts when modelling the demand linked to the supply provided by the legacy carriers or the LCCs?
e) How has the EU air transport market been developed since the last step of its deregulation process?

f) What are the main features and characteristics of this market?
g) How consumer confidence can improve the models built for estimating air travel demand for this market?
h) Does consumer confidence has different impacts when modelling the demand linked to the supply provided by the legacy carriers, the charter airlines or the LCCs?
i) What is the difference in the effects of deregulation between the Domestic US and the EU air transport market?
j) How has the EU-US air transport market been developed in the last decades?
k) What are the main features and characteristics of this market?
l) How consumer confidence can improve the models built for estimating air travel demand for this market?
m) Does consumer confidence has different impacts when modelling the demand linked to the supply side?
n) What are the reasons for the different results found in each case study?

1.3.2 Thesis layout

The introduction in Chapter 1 provides the research background relating to the subject of this thesis, as well as the aim and objectives of this study including the key research questions that are addressed. The research structure and thesis layout are also detailed.

Chapter 2 provides a comprehensive review of the different existing methodologies and associated methods or techniques used to forecast air travel demand as well as their use.

Chapter 3 identifies the different theories of consumption, defines the consumer confidence concept and provides a literature review and discussion regarding the forecasting power of a consumer confidence index in a consumption equation. The link is also made with air travel demand characteristics.

Chapter 4 details the methodological approach of the thesis and reviews the determinants of air travel. The process used for each case study of the thesis is explained as well as the forecasting issues linked to the forecasting technique that has been chosen.

Chapter 5 relates to the first case study, the US Domestic air travel market and analyses its different phases of growth, its air travel demand levers, its supply side segmentation and the impact of the US economic picture on air travel spending. It describes the two US consumer confidence indices and develops the models and resulting forecasts for air travel demand including the confidence index as an explanatory variable.

Chapter 6 relates to the second case study, the European air travel market and analyses its specific market context, its air travel demand levers and its supply side segmentation. It describes the respective evolution of air travel demand and consumer confidence index and shows the forecasts for air travel demand including the confidence index as an explanatory variable.

In chapter 7, the third case study, the EU-US air transport market is analyzed. The legal framework is described as well as the specificities of this market and the constraints associated to its supply side segmentation. The models and resulting forecasts for air travel demand including the confidence index as a potential explanatory variable are also discussed.

Chapter 8 provides a summary of the thesis conclusions and formulates recommendations for further academic research, while clarifying the contribution and limitations of this research.

2. AIR TRAVEL DEMAND

2.1 Forecasting air travel demand

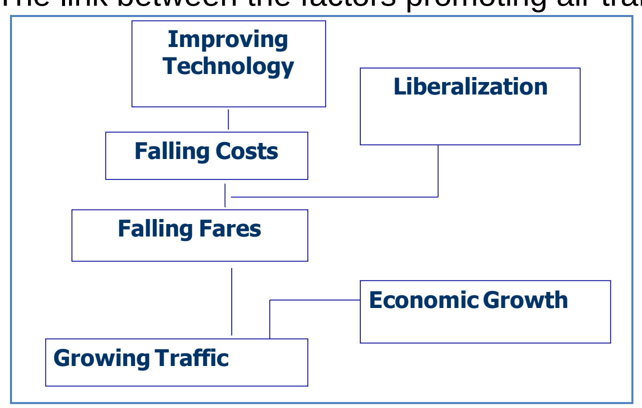
Both Airbus and Boeing's traffic forecasting methodologies are based on econometric models of causality that are unquestionably the most sophisticated type of forecasting method used today and by far the most frequently used method for forecasting aviation demand (Wensveen, 2007). This assessment was already stated almost 30 years ago by Taneja (1978) who argued that causal methods, particularly regressions, are the most popular methods of forecasting demand for air transportation.

These models are mathematical representations and unconstrained forecasts of air traffic, measured in RPKs, and independent variables supposed to affect air travel, GDP being the main driving factor behind growing demand for air travel.

In the process of developing air transport forecast, assumptions have to be made regarding the forces that will influence air travel demand. Factors affecting air travel demand can be grouped into two broad categories; socio-economic and transport (Taneja, 1971). Socio-economic variables are those inherent to the general economic, geographic, social and political environment, while the transport ones are those inherent to the transport mode, such as cost, travel time, comfort, safety and convenience. The volume of passenger traffic is influenced by a complex interaction of one or more of these variables.

Hence, forecasting air travel activity, even at a global market level, is becoming a complex process, as there are different forces at work, some promoting (schematized in Figure 5), others constraining air travel growth (Calvano, 2003).

Figure 5: The link between the factors promoting air traffic growth



Source: ICAO

These factors are either external or within the air transport industry. They are basically long range economic, social, demographic, and political trends, for example, the age and income distribution of its population, its ethnic and cultural ties to other nations (BCAC, 1993). Similarly, short-term conditions such as inflation, interest rate and currency exchange rates can have a strong effect on the growth potential of the total industry. The factors listed here below are reflecting the great majority of these forces:

- Factors related to the demand component of air forecasts, such as GDP trade, personal income, adult population, economic outlook and airline fares or yield
- Factors related to the operating strategies of the airline industry which represent the supply component of the air traffic forecasts, such as fleet, route structure, average aircraft size, Load Factors, labour costs and productivity, fuel cost and efficiency and other airline costs
- Factors representing potential structural changes that could stimulate or decrease future air travel demand, such as passenger traffic allocation assumptions and new technology

In recent years , the trend has been to take into account these forces by developing causal models that not only predict traffic but also determine the impact of changes within the economic environment (Abed, Ba-Fail and Jasimuddin*,* 2001*)*. They found that population size and total expenditure are the main determinants of international air travel in Saudi Arabia.
In a 2009 study, Oum et al made an important point that the liberalization of air service agreements leads to expansion in markets, but it also leads to more efficient continental and international networks which further stimulates traffic growth. The indirect efficiency effect would reinforce the direct effect of liberalization on opening markets. The degree to which this would occur depends on the extent of liberalization and the way it is done.

However, since forecasting models are relatively simple descriptions of very complex systems, they cannot account for all the political, social, psychological, and economic factors and their interactions that will lead to a particular set of outcomes.

The academic literature on air travel forecasting is reporting numerous methods and techniques that have been implemented in building models, and the following discussion is a literature review of the main forecasting tools that may apply to aviation demand forecasting.

2.1 Forecasting methods and techniques review

The techniques for forecasting air travel demand can be broadly classified into three categories (Taneja, 1971): judgemental, mechanical and analytical. The choice of a forecasting method should be based on several factors, including availability of data, accuracy of available data, management sophistication, intended forecast use, and availability of electronic data processing. There is a need to make a reasonable assessment of the time and cost of a sophisticated

forecasting method when related to data quality and to the management ability to use the results.
Based on a similar segmentation provided by Wickham (1995) quoting that the forecasting techniques used by airlines can be divided into three broad categories, namely quantitative, qualitative and decision analysis *(*combination of the first two methods), the following review of forecasting methods is far from exhaustive, but it suggests the range of available techniques. It is noteworthy that the wording used by different researchers is referring equally to forecasting methods or techniques.

2.1.1 Quantitative techniques

a) Causal methods

Causal methods range from regression models to simulation and spatial equilibrium models as well as to Bayesian analysis. Regression analysis is the most popular method of forecasting demand for air transportation (Taneja, 1971). The value being estimated, the dependent variable is related to other independent variables, the explanatory ones that “explain” the estimated value. Forecasts of the independent variables are used in the regression equation to calculate forecast values for the dependent variable. Generally speaking, regression models for aviation demand use economic variables like income, population, and employment rate.

Gravity models can also be listed under the causal methods (Swann, 2008). They use the size of the origin (city or country) times the size of the destination as an indication of the demand between them. Sizes are measured in population, or more usefully in GDP or even total air travel. The term “gravity” comes from similarity of the model to the product form for attraction between two masses. As in physical gravity, some measure of the distance between the masses is used so the attraction is less at greater distances. For travel, “distance” can be measured in kilometres, travel cost, travel time, or the amount of intervening destinations. However Swan (2008) warns that they predict demands both unreasonably larger and noticeably smaller than the historical traffic levels.

Another technique, the market-share model, is based on estimating a proportion of the regional or national level of activity assigned to the local level, usually assumed to be a regular predictable quantity. In this method, the existence of a data source minimizes the cost of forecasting but it neglects abnormal growth factors at the local level (Uddin et al, 1986). This method, however, lacks any statistical measure (Moutinho et al, 1998).

Consumer interviews which involve questioning current or prospective customers on projected purchases of the firm’s products under different conditions relating to price, income, competition, products and advertising is also used. By aggregating the data collected on all relevant variables the firm can estimate its demand function. The information obtained however, is likely to be of doubtful quality (Nicholson, 1995) since only hypothetical situation is used (Landsburg, 1991).

b) Time series analysis

A time series is a time-ordered sequence of observations of a variable. Time series analysis uses only the time series history of the variable being forecasted in order to predict future values.

Trend projection is the oldest and simplest application of time-series analysis in which time is the only independent variable. Time series analysis tools include also ratio analysis, moving averages, spectral analysis, adaptive filtering, exponential smoothing and Box-Jenkins (BJ) procedure. This technique produces a forecast based on a time series analysis of observations in which the most weight is given to the most recent observation and decreasing weights are given to earlier observations. This would give more weight to the latest trends and conditions on a sub-market, as it could be the case for a newly liberalised market. Time-series analysis is considered especially useful in producing short-term forecasts of monthly, weekly, daily, and hourly variations in demand. In that context, the BJ approach is useful for the statistical analysis of time because these two researchers sorted in a systematic manner all the statistical tools useful for the analysis of time series in their monography (Box and Jenkins,1970).

According to Taneja (1971), pure time-series is considered "generally statistical." This implies that, from a forecasting point of view, methods in this class may answer the "when" question, but do not address the "why" question. Taneja explains notably that these methods may, for example, be able to predict quite accurately the level of airline passenger demand in a certain year but not explain why it will be at that particular level. These methods cannot, for example, assess the impact of a reduction in fares, the introduction of new aircraft, an economic recession, or the uncertainties associated with the future labour climate.
He contends that such questions can only be answered if the forecaster has specified and calibrated a formal model that shows the influence of all the relevant variables and not just one (time), as it is the case for most of the time series analyses.

2.1.2 Qualitative techniques

Judgmental methods are based on intuition and subjective evaluations and they include judgmental forecasts, expert opinions, sales force opinions and poll forecasts . Although they are the least rigorous types of forecasts, they are frequently a powerful factor in decision making. They can be used when either no information or very little historical data exist. They can also be used to adjust forecasts developed by causal models or through time-series analysis.

The most famous judgmental method is “Delphi” consisting in attaining consensus forecasts among experts. With Delphi, initial estimates are obtained from each expert. After one or more rounds of comparison and feedback, judgements begin to converge and consensus forecast is reached.

The usefulness of expert opinion, sales force opinion, or polls depends on the cost, availability, and reliability of these types of data. In the sales-force estimates approach sales personnel who are in direct contact with customers are considered to be in the best position to estimate likely short-term sales. Their estimates however, are often revised at a higher level (Makridakis 1990).

For cases in which buyers do not plan their purchases carefully or are very erratic in carrying out their intentions, or in which experts or the sales force are not particularly good guessers, a poll or survey of buyers' intentions is preferable. A poll or survey also is generally more desirable in forecasting the market for a new product or for an established product or service in a new territory. The surveys are specifically aimed at establishing the travel patterns of air travellers to determine where they originate or terminate their trip in a region, their trip purpose, and their relevant socio-economic characteristics. Examples of survey techniques include questionnaires given to travellers, data collected from travel agents, and license plate surveys at airport parking lots.

When a short-term forecast of likely buyer response is desired, an expert opinion may be called for.

2.1.3 Decision analysis techniques

They include Market Research, System Dynamics, Heuristic and Probabilistic methods. Tsekeri (2009) has also estimated the short and long-term response of air passengers to change in relative air-sea travel cost components in competitive markets using a dynamic demand model. The model demonstrated the importance of considering the past volumes of air passengers and relative travel cost components to explain current air travel demand (Postorino, 2003).

In addition the decision analysis techniques cover also combination of the two previously mentioned techniques or alternative solutions. For instance when dealing with uncertainty (in order to cover possible external shocks), a range of forecasts can be developed by using scenario forecasts, which may have high and low forecasts, with a "most likely" level included.

Another approach when dealing with a large group presenting different components is to use the Cohort analysis. It makes sense, for a specific sub-market to disaggregate the historical flow of passengers into major groups, such as individuals travelling for leisure purpose, those for business purpose, those attending a convention, and local residents on personal travel. Then a separate analysis can be made of the likely factors that underlie the passenger demand of the separate cohorts.

Another technique consisting in comparison with other markets can also be used. In this technique the analyst compares the market to be forecast with other markets of relative size and relevant characteristics. One particular use of this technique is in projecting future market growth after a major change such as the addition of a Low Cost Carrier supply segment. In this case, analogy can be made to growth rates achieved at similar markets after they obtained initial low-fare carrier service.

Among other decision analysis techniques, it is worthwhile mentioning the Share Analysis and the Choice and Distribution Models. In the first one, historical market shares are calculated and used as a basis for projecting future shares. This approach is a “top-down” method of forecasting since forecasts of larger aggregates are used to derive forecasts for smaller areas, such as a country to country forecast being derived from a regional air travel market forecast.

In the latter, the important elements are an adequate database and knowledge of the structure of traveller choices. In the context of airport choice, the full price of travel may depend on economic characteristics related to each airline competing in a market: cost of airport access, type, and availability of air services, and their cost as well as attributes that are specific to individual consumers such as income or trip purpose. An important assumption of many choice models is that the overall size of the market is fixed.

However, despite these different forecasting methods and techniques, there are still a great number of issues not yet solved, notably, how to deal with the future of the networks, the evolution of the average aircraft size, the non-use of great number of drivers affecting the market and the modeling of the non-satisfied demand in the past, due to a non-adapted supply offer. Bontemps (2003), defines real demand as the sum of the satisfied and the non-satisfied demands. While it is easy to collect data (e.g. number of travelers, number of passengers-kilometer or number of ton-kilometers for freight) measuring the satisfied (historical and current) demand, it is difficult to evaluate the true real demand. Indeed, among the factors affecting individual demand, apart from the quantitative factors such as income, price or global transport duration, there are various qualitative ones characterizing the supply side and affecting the air travel demand which are difficult to evaluate, such as quality, flexibility, availability or flight frequencies.
In the last 20 years, and from the supply side of air transport, it seems that new airlines business models, notably the so-called LCCs are influencing the market and have answered to a non-satisfied demand by offering a more adapted supply, either through lower fares on an existing route (e.g. Paris - Dublin : traffic multiplied by 3 in 5 years after the arrival of Ryanair) or through the opening a new route (e.g. Biarritz - London : around 100 000 passengers the first year), enabling more people to afford air travel. As this demand (non-satisfied) has been created by a new supply side, it was not possible to identify it under the historical pattern which was modeled under a non-adapted supply.
The empirical literature shows that LCCs such as Southwest Airlines play an important role in determining the shape and structure of the market (Morrison, 2002). Southwest has traditionally captured market shares by offering low prices for less differentiated travel services, or what has become known as spoke-to-spoke services. Thus, the entry of Southwest in a market may have two impacts: first, a substitution effect of lower fares where air travelers switch from the services

offered by a legacy carrier to services offered by LCCs, and second, a complementarity effect where lower prices of Southwest may actually induce more travelers into using air transportation as opposed to other modes, especially those in the short-haul markets (i.e., less than 1500 miles of stage length). This latter effect may benefit both Southwest and other airlines thus establishing complementarity, according to Bhadra (2003).

In light of the above, it is necessary to forecast demand in order to adapt the supply (and vice-versa), should it be for the airlines in terms of network optimization, revenue management and fleet or for the airports and the air navigation service providers in terms of infrastructure planning.

2.2 Adapted forecasting methodologies for each need

Each type of forecast serves a particular purpose and are developed under different time spans. Forecasting passenger enplanements for a one-year period on well-established routes, possess a fundamentally different forecasting problem than estimating enplanements on a new route, and forecasting methods must be chosen accordingly.

Therefore, Civil Aviation Authorities (CAAs), airlines, airports, specialised publications, international organisations such as IATA, or the International Civil Aviation Organization (ICAO) and aircraft manufacturers are not using the same methods as their objectives or their needs could be divergent.

Short-term forecasts normally span a period of one month to one year and cover such day-to-day operations as staffing stations, evaluating current competitive situations in the market, and projecting short-term equipment needs. Thus, an airline might make a short-term forecast of total passenger enplanements between a particular pair of cities to provide a basis for determining station personnel and ground equipment needed, gate availability, and expenses related to these items.

Medium-term forecasts generally span a period of one to five years and involve such things as route-planning decisions, while a long-term forecast spans a period of 5 to 20 years and might involve fleet planning decisions and long-term financial commitments. An aircraft manufacturer might make a long-term forecast of demand for a new type of aircraft designed to serve a specific market and then plan to produce it in order to meet the projected demand.

2.2.1 Civil Aviation Authorities

As an example of what is used by aviation authorities in matter of forecasting, the Federal Aviation Administration (FAA) approach is based on a decision-theoretic forecasting system built first with causal models, as explained in their FAA Aerospace Forecast for the Fiscal Years 2011-2031. Initially, projections are made with the use of econometric and time series models. The model equations and outcomes are then adjusted based upon "expert industry opinion" to arrive at subsequent forecasts for use in the decision-making process.

2.2.2 International Organizations

As an International Organization, IATA uses a variety of forecasting methodologies depending on the issue and time span should it be short, medium or long term. IATA's short term forecasts are developed on a monthly or quarterly basis, using times series techniques or judgmental approaches based on surveys. For instance, the latters are performed using purchasing managers buying intentions (PMI) to forecast FTKs, and consumer confidence surveys to forecast RPKs. Their medium term forecasts, are developed with causal forecasting models, using econometrically estimated parameters, as explained in their CD Airline Industry Forecast 2010-2014. The annual survey of airlines' own forecasts is used to establish the airline "consensus" forecast which is based on the Delphi technique discussed in the previous section. For the development of its long term (and very long-term) traffic forecasts, IATA uses structural forecasting models calibrated largely on theory-derived parameters such as propensity to travel which is linked to income, as described in the 2008 IATA Economic briefing (Air Travel Demand).

On the other side of the street in Montréal, the United Nations (UN) specialized agency, ICAO, has developed a new methodology (switching from a top-down to a bottom-up approach) for their traffic forecasts, to be officially released in December 2012 in a new publication, Global Air Transport Outlook (GATO) for 2030. In the GATO, ICAO produces 20 year forecasts of air traffic to support aviation planning throughout the world. The world is divided into nine geographical regions and forecasts are developed for 30 route groups (18 inter-regions, 5 international within each region and 7 regions domestic) for scheduled traffic. Total non-scheduled traffic for all regions is also modelled as a single market. The forecasts are developed under the econometric modelling technique. The forecasts of international passenger traffic by route groups are further allocated among airlines of each region, following a judgmental technique based on experts opinion. This allocation uses historical data, and the analysis of competitive airline advantage, financial strength, fleet plans and other considerations. Passenger traffic forecasts, expressed in terms of RPKs, are also converted into forecasts of aircraft movements by using assumptions (based also on experts opinion) on future average load factors, average aircraft seating capacities and average distance stage length for each selected route group.

2.2.3 Specialized entities

Among the various traffic and fleet forecasts issued by different specialized entities, it is worthwhile mentioning *The Airline Monitor* which is a specialised magazine that (among other outputs) projects worldwide demand for commercial jet transport aircraft[5]. The time frame of the forecast is approximately 20 years, with the objective to overlap the time period of similar forecasts prepared by the main aircraft manufacturers. A traffic forecast is prepared for each major region of the world and the key driver is the near and long-term expectation for the growth rate of GDP measured in real constant-dollar terms. In addition, for the most developed sectors, namely US and Europe, it is assumed that the price of air travel is also a major driver of demand. Therefore a multiplier is applied to the percentage change in real yield. The resulting number of yearly RPKs in each region is summed to obtain a world traffic number for each year of the forecast period.

2.2.4 Aircraft manufacturers and Original Equipment Manufacturers (OEM)

Forecasts of future world demand for commercial aircraft are published fairly regularly by Airbus and Boeing, as well as other engine manufacturers such as Rolls Royce. The methods used and assumptions made by the several forecasters were analysed by Anker (2000) and he concludes that there are wide areas of similarity in the approaches used. The two major civil aircraft manufacturers are modelling individual market segments and then aggregating them, in order to produce a more accurate overall picture than treating the demand for air travel as a whole single market. The results of this bottom-up methodology are published in the Global Market Forecast (GMF) developed by Airbus and the Current Market Outlook (CMO) released on a yearly basis by Boeing. Airbus and Boeing's traffic forecasting methodology are based on causal models and for the majority of the sub markets, the forecasting process is the same before obtaining a global world traffic forecast, thanks to the aggregation of all the results. According to Swan[6] (2008), it is known that the Airbus forecasts are based on GDP-trend regressions mentioning that there is some "massaging" of the forecasts when high GDP growth implies unreasonably high final levels of world or regional travel. He concludes that the Airbus forecast for the world is nearly the same as the Boeing forecast, as they are producing trend forecasts. Although a trend forecast has the advantage of not forecasting against the pattern of recent history, it cannot forecast change, but it can be superior where changes are not expected. Therefore, it renders the forecast less valuable.

Poore (1993) conducted a study to test the hypothesis that forecasts of the future demand for air transportation offered by airplane manufacturers and aviation regulators are reasonable and representative of the trends implicit in actual experience. The tests compared forecasts issued by Boeing, McDonnell Douglas (now integrated in the Boeing Company), Airbus Industry (now Airbus) and ICAO with actual data and results of a baseline model of the demand for RPKs. He found that the results were in the range of a high and low scenarios compared to his baseline model.

[5] http://www.airlinemonitor.com/ accessed July 2011
[6] William Swan was Chief Economist in Boeing Commercial aircraft from 1996 to 2005

The major issue in accurately predicting demand for air traffic in the short term is subject to factors that no econometric forecasting model could accommodate, such as wars, terrorist action or a high fuel price. The aircraft manufacturers are predicting average trend growth, on a twenty-year vision, and hence they are unable to catch an accurate picture of the possible short-term.

Therefore it seems interesting to investigate how to supplement this long-term vision, by accurately estimating the short-term fluctuations that could be closely related to qualitative factors which are not currently taken into account in the traditional quantitative factors used to forecast long-term air travel demand.

3. ECONOMIC INDICATORS AND AIR TRAVEL SPENDING

The effect of consumer attitudes on consumption and economic activity is a subject of great interest to both policymakers and economic forecasters,

Based on an analysis (from 1960 to 2007) of a panel sample of 145 countries (Furceri and Sousa, 2009) conducted with the objective to assess the impact on private consumption and investment of changes in the ratio government spending over GDP, it was found that private consumption is a very important component of GDP representing about two thirds (68.22%) of GDP. Indeed, among the various components of GDP, consumption is by far the largest one (Lequiller and Blades, 2006). Therefore, a good understanding of consumption behavior is important to determine if the ratio of consumption to income is stable, and why variations do occur.

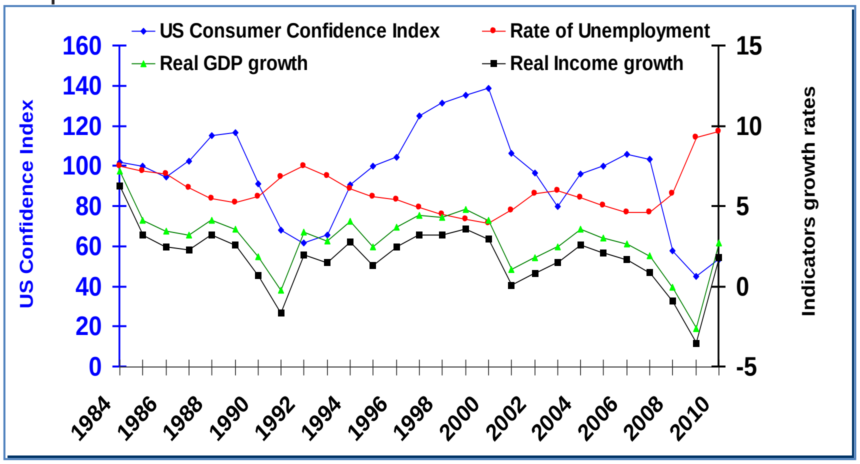
A dedicated indicator has been designed to measure consumer confidence, which is defined as the degree of optimism on the state of the economy that consumers are expressing through their activities of savings and spending. Such measurement is indicative of the consumption component level of the GDP. Consumption may be divided according to the durability of the purchased objects, and in this vein a broad classification of consumption separates services such as air travel from durable goods and from non-durable goods. These three categories often show different paths of growth, and changes in overall consumer spending are likely to be driven more by spending on durable goods and other discretionary items (such as air travel spending for leisure purposes) than by spending on essential items, during the course of an economic cycle. Besides, periods of high economic or political uncertainty are often associated with high volatility of consumer confidence, suggesting that large swings in confidence are also particularly important for discretionary expenditures. In addition, strong variations in confidence are assumed to be likely driven by major events that are thought to strongly affect household mood, and are often followed by fluctuations in GDP. Therefore the consumer confidence indicators are supposed to determine consumption patterns especially in the occasion of exceptional circumstances.

3.1. The Consumer confidence concept

The concept of sentiment index appeared on the US economic scene, as part of a survey devised by Katona (1975) to investigate the determinants of the financial decisions of households, in order to measure, understand and analyze the impact of changes in consumer attitudes and expectations. The consumer confidence index (CCI) is constructed to measure these attitudes and is supposed to reveal the potential impact of households' behaviors, in terms of emotional attitude, on spending, notably during particular events or in times of uncertainty about future financial and economic situation. To measure such attitudes, surveys are conducted and the results of these surveys are then arranged into "balances", calculating the differences between the percentages of positive and negative answers, in order to build a composite indicator.

Based on the US economic indicators, there are positive correlations between the move in the confidence index and real GDP and income growth, and an inverse correlation with changes in the unemployment rate. Given the reasonably close relationship shown in Figure 6, confidence surveys are often considered as indicators of current and future consumption prospects.

Figure 6: Comparative evolution of some US economic indicators vs US CCI



Source: IHS/Global Insight

The first survey of consumer confidence was developed in the USA by the University of Michigan in the forties, while in Europe, the importance of qualitative surveys on consumer attitudes was not perceived until the early seventies, under the influence of the American experience and in the context of a sharp increase in inflation and a high unemployment rate.

In 1972, the European Community (EC) launched a harmonized consumers´ survey, to be run three times a year, initially limited to Germany and France and then extended to Belgium, Italy and the Netherlands, while now it is extended to all the EU States.

Although, consumer confidence is perceived as an important and informative predictor of forthcoming economic changes, alongside typical macroeconomic variables like interest rate spreads and money supply, in the literature, there is a lack of a theory (Dominitz and Manski, 2004) or of a precise definition of the concept of consumer confidence that could be applied to each CCI measured in each country. For instance, in the US, the Consumer Confidence Index published by the Conference Board is officially referred to as “a barometer of the health of the US economy from the perspective of the consumer”[7]. In Europe, the Business and Consumer Survey data are widely used by the European

[7] Conference Board Consumer Confidence Survey Technical Note (February 2011), available at http://www.conference-board.org/pdf_free/press/TechnicalPDF_4134_1298367128.pdf

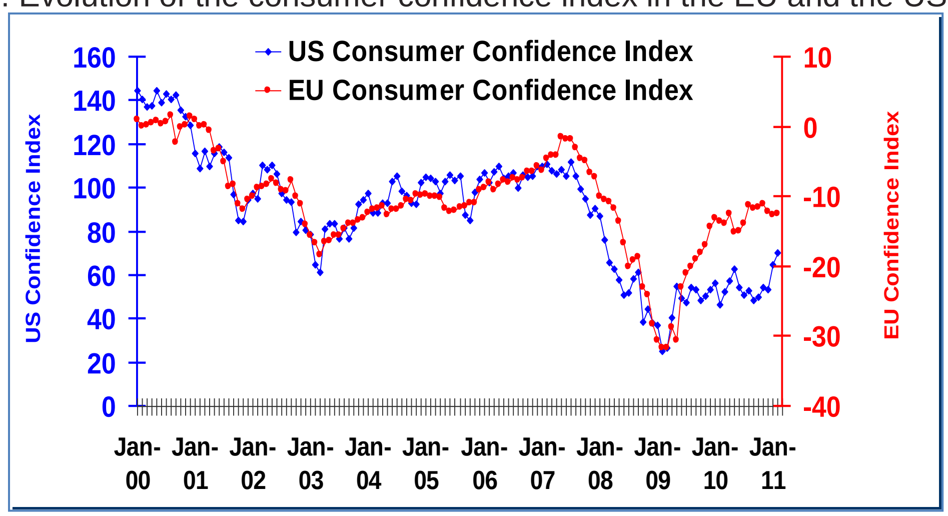
Commission (EC) for economic surveillance, short-term forecasting, and business cycle analysis (DG ECFIN[8], 2006). For instance, DG ECFIN considers the survey as "an essential tool to monitor the economic situation in the Member States, the euro area and the EU"[9].

However, consumer confidence is a somewhat common concept to US and EU countries, as both confidence surveys typically ask for a variety of questions that capture household perceptions of different economic factors. Positive responses to these questions are likely to be associated with households feeling more confident. The Consumer Sentiment Index (CSI) which is produced by the University of Michigan in the US and the European Commission (EC) survey are based on very similar questions.

Today, these indices are very popular, being currently reported on the media and largely commented by economic analysts. This strong interest is essentially due to the fact that they are released in a timely manner and are the only source of information on the evolution of the economy for a lapse of time, during each month.

Figure 7 shows the confidence measures for the two different economies. Both of them follow a broadly similar pattern, consistent with the somewhat synchronised developments in the two areas over the past twenty years. The US and EU consumer confidence indices seem to be related to the same macroeconomic factors but there are substantial differences in shorter-term movements, reflecting factors specific to the state of each economy.

Figure 7: Evolution of the consumer confidence index in the EU and the US



Source: IHS/ Global Insight and European Commission

Another view sees confidence as a measure of happiness or mood. In that case, at the individual level, respondents answer the surveys in terms of their own

[8] DGECFIN: Directorate-General for Economic and Financial Affairs for EU
[9] http://ec.europa.eu/economy_finance/publications/publication7568_en.pdf

situation as regards to their neighbours and the last noteworthy recent events in the news. Confronted to a major political or social event, households modify their expectations on future economic conditions even though the current economic conditions did not require it. In special circumstances, consumer confidence may lose its correlation with general economic situation although it keeps its special relation with its short range of determinants such as unemployment rate and GDP. As soon as the special events dissipate, confidence goes back to its long-run relationship.

3.2. The Consumption pattern under different economic theories

Beyond the Keynesian theory which suggests that consumption depends primarily on current income there are different major theories, similar in their implications that try to explain households' consumption behavior.
This section reviews the economic approaches of consumption based on the Absolute Income Hypothesis (AIH), the Permanent Income Hypothesis (PIH), the Life Cycle Hypothesis (LCH), the random walk theory and the psychological approach of consumer expenditures, by trying to link consumer behaviour to the consumer confidence concept.

3.2.1. The Keynesian theory

As described by Palley in 2008, the Absolute Income Hypothesis is a theory of consumption proposed by Keynes in 1936 which identified the relationship between income and consumption as a key macroeconomic relationship. This theory asserts that real consumption is a function of real disposable income which is total income net of taxes. As income rises, consumption will also rise but not necessarily at the same rate. When applied to a cross section of a population, rich people are expected to consume a lower proportion of their income than poor people. The main well-known features of Keynes' analysis are that the marginal propensity to consume (MPC) which determines by what amount consumption will change in response to a change in income, falls with income, as does the average propensity to consume (APC) which is the percentage of income spent obtained by dividing consumption by income. While this theory has success in modeling consumption in the short term, attempts to apply this model over a longer time frame have proven less successful.

This has led to the Absolute Income Hypothesis falling out of favor as the consumption model of choice for economists.

3.2.2. The Life cycle hypothesis

The Life Cycle Hypothesis is an economic concept developed in the fifties analyzing individual consumption patterns. The LCH (Pesaran, 1987) considers that individuals plan their consumption and savings´ behavior over the long term and intend to even out their consumption in the best possible manner over their entire lifetimes. The key assumption is that all individuals choose to maintain stable lifestyles. This implies that they usually don't save up a lot in one period to spend furiously in the next period, but keep their consumption levels approximately the same in every period. Consumers then are likely to spend when young and old and save when they are middle aged so as to consume most of their resources over their lifetime. The LCH predicts that consumption depends on permanent income, which is the annuity of overall life time resources. The theory implies that consumption is unrelated to current income, and thus, there will be no role for consumer confidence in predicting actual consumption.

3.2.3. The Permanent Income Hypothesis

Very similarly, Friedman (1957) postulated that consumption was determined on the basis of an individual's income over his or her lifetime. Instead of focusing on the age of the consumer, Friedman focused on the type of income that the consumer received. He categorized income into two types, the permanent income which is income that people expected to last into the future and the transitory one which consists of temporary deviations from permanent income.The Permanent Income Hypothesis, as this theory is known, argues that consumers' expenditures are financed from their permanent income. Temporary gains in income do not affect consumption. This could explain why temporary tax cuts appear to have much smaller effects than permanent cuts (Steindel, 2001), stating that an individual divides his or her entire lifetime resources equally among each period of life. Consequently, a rise in income will increase consumption only to the extent that this rise reflects a gain in permanent income. If confidence anticipates income, then high confidence today should signal higher income in the future. Under the PIH, the fact that confidence anticipates expected income means confidence can be useful to explain current consumption.

3.2.4. The Random walk theory

Hall (1978) finds that, under perfect capital markets, the PIH can be approximated by a random walk, thus concluding that no past information other than consumption can help predict current consumption.
In 1989, Campbell and Mankiw assessed the random walk hypothesis by separating consumption into two types of consumers: life-cyclers and ´´rule-of-thumbers´´. The former consume from their permanent income whereas the latter consume from their current income. The authors find a share of about 0.5 for each type of consumers, thereby questioning the PIH. According to the random walk model, consumption should not respond to expected or predictable changes in income, since the decision on the current level of consumption should already have taken this expected change into account.

Even if recent work suggests instead that consumption depends on current income, expected future income, wealth and interest rates, all these theories assume that consumers are rational and act to maximize lifetime utility.
Overall, these theories leave very little room for sentiment to play a role in determining consumption. Some have even argued that consumer sentiment simply reflects other economic determinants of private consumption. According to this view, once the appropriate underlying economic determinants have been identified and properly measured, there is no additional information value in consumer sentiment.
More recently, additional studies were developed considering the psychology of consumers to understand consumer behavior.

3.2.5. The Psychological approach

According to the psychological approach (Katona, 1975) of consumption, consumer expenditures are tied both to the resources and the psychological attitudes of the buyer representing respectively, capacity and willingness to consume. The essential elements to consumer demand (Blanchard and Fischer, 1989) are desire for consumption and ability to pay for that consumption. The desire for consumption must contain the willingness to consume at the prices requested for that consumption. The willingness to consume diminishes as the price of such consumption increases, while this willingness increases as price reduces. Willingness to consume at a specific price can be designated as the desire to allocate a certain net percentage of the consumer income for a specific good or service. The allocation procedure, though, remains highly dependent on the economic factors which are related to both the level of income and the consumer’s perception of the state of his total (current and future) income. Therefore the consumer expenditure is linked both to the capacity to consume expressed notably through the consumer’s expectation of increase or decrease of total income and to his willingness to pay a specific price for an expense considering both its net percentage of his total income and the unavoidable expenses that he is expecting to incur. This actual alteration of product pricing and expense represents the first factor of the consumer decision for consumption, while a more subjective second factor is deeply influenced by its perception of the state of the total economy. Hence the willingness to buy is also influenced by non-quantifiable or non-economic factors such as political crises or wars.

Following this theory, the consumer confidence index is expected to represent the household “willingness to buy” and therefore is supposed to influence discretionary, infrequent and non-planned purchases, not strictly necessary for life.
In this paradigm, consumption depends on the confidence that individuals have regarding their future financial condition. The cornerstone of the psychological theory is that willingness to consume cannot be explained only by the reaction of consumers to economic variables. According to this view, a drop in confidence

can, by itself, cause a decline in consumption in a way not foreseen by economic variables, without for instance a decrease in income. The main factor behind the psychological approach is either present or expected uncertainty. Also, uncertainty relative to future income can be such that individuals opts for precautionary savings (Flavin, 1981) by reducing current consumption and building reserves in the advent of a drop in income. In addition, those precautionary savings can be affected by liquidity constraints. Even if the constraint does not bind currently, the possibility that it will bind in the future reduces consumption.
The concept of willingness to consume must be negatively related to uncertainty (Acemoglu and Scott,1994). More precisely, even if consumers' financial position is unchanged, higher perceived uncertainty relative to that position can lead to a drop in consumption, as higher uncertainty lowers marginal propensity to consume. In this context, the usefulness of confidence comes from its ability to convey consumers' assessment of risk. This assessment should affect spending plans only to the extent that this uncertainty translates into economic uncertainty. The psychological view's justification thus boils down to the need for precautionary savings.

Consumer confidence indices comprise three components: current conditions, future conditions, and total (current + future) indices. This decomposition could be helpful in determining the relative relevance of the two competing views, namely, if current conditions react only to a change in willingness to consume, or if future conditions react only to a change expected income. However, it is difficult to empirically distinguish the source of changes in confidence as each component can potentially react to a change in both expected income and willingness to consume or uncertainty. Changes in the willingness to buy are associated with the consumer's attitudes and expectations. This is because the consumer develops anticipations about his/her likely future economy and circumstances, and this becomes a piece of additional information used to decide whether he/she should spend or save now. Accordingly, consumers with optimistic expectations tend to spend more on discretionary goods and services and save less, whereas consumers with pessimistic expectations tend to spend less and save more (Van Raaij, 1991).

An assessment of whether confidence proxies expected income, or whether it provides additional information can be done, for instance, by regressing confidence on future income. This has been done for Canada by Côté and Johnson in 1998, who found that about a third of the movement in confidence can be explained by its correlation with changes in leads of income.

3.2.6. The EU and US confidence indices

When trying to test the forecasting value of consumer confidence in different markets, it raises the question of the consistency between each consumer confidence measurement.

It is noteworthy that the US and the EU indices do differ in terms of the questions asked in the survey, the sample size, and construction. However, the

US CSI is built on the aggregation of sentiment indices measured in four geographic regions, namely North East, North Central, South, and West, and it is similar in the EU aggregation process which measures the confidence index for several countries before computing the global EU confidence index.
For the EU countries the EU CCI is derived from the national CCIs that are calculated using information collected from surveys that ask the same questions across all EU countries. Responses are collected during the first 10 working days of each month. The CCI composite Index of each country is based on four forward-looking questions:

- *(Qi)* over the next 12 months, how likely is it that you save any money?
- *(Qii)* how do you expect the financial position of your household to change over the next 12 months?
- *(Qiii)* how do you expect the general economic situation in this country to develop over the next 12 months?
- *(Qiv)* how do you expect the number of people unemployed in this country to change over the next 12 months?

Each question can be answered in six ways: get a lot better (PP), get a little better (P), stay the same (S), get a little worse (M), get a lot worse (MM), and finally "I don't know" (N). For each of the four questions, a balance B = (PP + ½P) − (½M + MM) is calculated, where PP, P, M and MM represent the percentage proportion of answers in each category. These balances are averaged to calculate the country composite CCI:

$$CCI = (Bi + Bii + Biii - Biv) / 4.$$

In the US, the CSI is published by the University of Michigan's Institute for Social Research[10] and is based on answers to the following questions:

- (*Qi*) would you say that you (and your family living there) are better off or worse off financially than you were a year ago?
- *(Qii)* do you think that a year from now you (and your family living there) will be better off financially, or worse off, or just about the same as now?
- *(Qiii)* now turning to business conditions in the country as a whole, do you think that during the next twelve months we'll have good times financially, or bad times, or what?
- *(Qiv)* which would you say is more likely: that in the country as a whole we'll have continuous good times during the next five years or so, or that we will have periods of widespread unemployment or depression, or what?
- *(Qv)* do you think now is a good or bad time for people to buy major household items (e.g., furniture, refrigerator, stove, television, and things like that)?

[10] In the Consumer Confidence Survey published by the Conference Board, the forecasting questions ask about subjects' expectations over the next six months (not 12 months) and do not refer to 'country wide' conditions but to conditions 'in the area'. Moreover, the questions have only three possible answers: positive, negative and neutral.

The retrospective element of the CSI is not the only difference with the EU CCIs. The CSI monthly surveys are collected over the entire month (not 10 working days as in the EU counterpart) and aggregated in a different way. Besides, there are only four possible answers to each of the five questions: get better (P), stay the same (S), get worse (M), and “I don’t know” (N), while in addition, for each individual question *i* a relative score (X_i) is calculated as $X_i = PM + 100$, where P and M refer to the percentage of respondents choosing ‘get better’ and ‘get worse’ respectively. In this way the index for each question is always positive because there cannot be more than 100% people responding negatively to each question. The scores are rounded to the nearest whole number. The CSI is calculated as a linear transformation of the sum of the individual question relative scores, as shown in equation (1):

$$CSI = 2 + (1/6.7558)\sum X_i \qquad (1)$$

where 6.7558 is the 1966 base period total, and the constant ´´2´´ is added to correct for the sample design changes from the 1950s.
Although the CSI and the EU CCI are not directly comparable, the CSI can be seen as a linear transformation of the EU CCI[11]. As such first differences of the CSI is equivalent to first differences of the CCI (times 5/6.7558) subject to differences in the nature of questions and possible answers.

According to a study published in the Federal Reserve Bank of St Louis review (Garett, 2004), consumer sentiment may help assess the general state of the national US economy, but it seems not to be an important factor in forecasting regional consumption.

For the EU countries, a similar study (Taylor and Mc Nabb, 2007), in the original 15 EU countries, showed the same finding.

However for both markets, it is still difficult to feature why these aggregated indices would then influence macro consumption.

3.3. The forecasting power of the Consumer Confidence concept

The consumer confidence concept is related to a set of macroeconomic variables that changes over time on a monthly basis. The qualitative responses to consumer survey in a coded quantitative index form provide information that enables to determine their influence on consumption patterns. As reviewed in the below section, numerous analyses of consumer confidence indices within a consumer spending forecasting equation have been conducted during the last fifty years, leading to controversial results.

3.3.1. Usefulness of the confidence index in consumption forecasting

The idea that indexes of consumer confidence may be useful in forecasting

[11] Note $CSI = 2 + 500/6.7558 + 5/6.7558\,(\sum(P_i - M_i)/5)$

consumption was first proposed by Eva Mueller (1963), who used ten years of data from the University of Michigan survey of consumers. She found that consumer confidence was a significant explanatory variable for consumption spending in a regression that included lagged consumption in the equation. Frederic Mishkin (1978) found that the significance of the Michigan consumer confidence measure depended on what else was included on the right-hand-side of the equation for prediction spending on durable consumer goods, as for instance adding financial variables to the equation greatly reduces the explanatory power of consumer confidence. Van Raaij (1991) argued that the expectation of a household's personal financial progress and economic situation influences buying decisions, especially for durable goods, vacations and recreation, as well as saving decisions. Christopher Carroll, Jeffrey Fuhrer and David Wilcox (1994) confirmed Mishkin's finding for overall personal consumption expenditures, noting that the explanatory power of the confidence index declined after 1978.

On another hand, Jason Bram and Sydney Ludvigson (1998) tested the Michigan index against the Conference Board index and found greater explanatory power in the Conference Board's index. They also ran out-of-sample forecasting exercises, finding that the Conference Board's index reduced the root-mean-squared forecast error (RMSFE) relative to a baseline forecasting equation in which consumption spending growth is forecast with its own lags, and lags of income growth, growth in real stock prices, and the change in the interest rate, while the Michigan survey increased the RMSFE. However, neither change in RMSFE was statistically significant.

More recently, Philip Howrey (2001) tests whether the Michigan survey helps predict business cycle turning points and consumption spending. He finds that the monthly information in the confidence index helps improve quarterly forecasts, so the high-frequency information in the Michigan index appears useful.

Besides, Vuchelen (2004) showed that the inclusion of the survey data improve the predictive power of a model, when compared to predictions made with traditional economic variables only, as the consumer sentiment reflects some subjective moods, intentions and private information of the consumers, which embodies the information in the macroeconomic and financial variables, but also contains information that cannot be directly deduced from them.

When related to the traditional economic theories of consumption linking changes in income to predictable changes in consumption, the usefulness of consumer confidence indicators can only come from the fact that they capture information relative to expected income, but that current consumption cannot react because of liquidity constraints. Therefore, consumer confidence can be seen as indicator of liquidity constraints.

Few studies have found that confidence indices have significant explanatory power once fundamental economic factors are taken into account. Even more, a certain number of researchers stated that consumer confidence indices are of negligible value because they lose their explanatory power with the addition of control variables.

Finally, some researchers, Garner (1991) and Throop (1992) performed event studies and suggested that the consumer confidence indices could be helpful during major economic or political events, as in that circumstances, they tend to diverge from a path consistent with other macroeconomic variables. Indeed household sentiment has been cited as one of the leading causes of the 1990/1991 recession, while unexpected shifts in consumer confidence have also been used to explain swings in financial markets.

In parallel, similar analyses (Fei, 2011) and (Fagan, Henry and Mestre, 2001) on the role of the consumer confidence index in Europe, seem to support the view that it has some autonomous forecasting power.

Others researchers (Easaw and Heravi, 2004) have shown that these indexes may also be fruitfully used in the specification and estimation of consumption functions in Europe.

Finally further assumptions are suggesting that the confidence indexes might prove to be even more useful in real time than they were with latest available data. These data revisions are based on information not known to government data collectors until after the fact, but people know about their own incomes and their own spending plans when they respond to the surveys of consumer confidence. This raises the question of whether these indexes are valuable for forecasting consumer spending in real time and if they are more valuable when combined with real-time data than if combined with latest available data.

3.3.2. Use of the confidence index in other industries

Adams (1964) found that the consumer sentiment was useful for forecasting motor vehicle expenditures; however, they also found that stock prices were a reliable substitute for the survey measure.

Hymans (1970) used the consumer sentiment as a predictor in a forecasting equation for automobile spending, with significant results. Hymans also estimated automobile expenditure by splitting the CSI into its predicted values and the residuals from the first regression. He found that there is little change in the coefficient estimates although the standard errors on the residual were much larger reducing its statistical significance.

Later studies (Fair, 1971) and (Juster and Wachtel, 1972) supported Mueller's claim that sentiment could predict other durables as well.

Van Raaij (1991) argued that the expectation of a household's personal financial progress and economic situation influences buying decisions, especially for durable goods, vacations and recreation, as well as saving decisions.

Boehm and McDonnell (1993) argued that the consumer sentiment index performed well as a leading indicator of retail trade, consumer durables and new passenger vehicle registrations. Similarly, Easaw et al (2005) revealed that the UK confidence index has some predictive powers in forecasting durable, non-durable and service consumptions the UK.

Gelper et al (2007) discovered that the CSI can predict US consumers' spending on services better than durables or non-durables in the long-run.
In 2009, Allen and Yap assessed whether the consumer expectations of the future economy can influence tourism demand for a destination based on the assumption that an increase in consumers' optimism about the future economic outlook may lead to a growth in the demand for tourism. Overall, they confirmed that the income and tourism price variables are still the important determinants of Australian domestic tourism demand. However, they found that to a certain extent, other variables such as consumer sentiment index can play an important role in influencing Australians' decisions to travel domestically.

The main issue in the context of forecasting purposes remains in the availability of forecasts of consumer confidence indices. Tracking the periods when consumer confidence drifted away from its economic determinants provides an insight into its determinants and Adams and Green (1965) remarked long ago, the wish to predict consumer confidence would require forecasting its components. Alternatively, it would also be possible to predict directly consumer confidence thanks to T-1 data. This assumes that the determination of the expectations necessitates some time corresponding to the learning process, during which consumers take into account the latest economic news mixed with their own experience and draw their own conclusive picture. However, as this lag is short and represents less than a quarter, it restricts its use as forecasting period.

In addition, as economic growth is tied up with consumer demand, which in its turn depends primarily upon household income and is also affected by consumer confidence (how optimistic or pessimistic consumers are feeling), these intertwined relationships are similar to a causal loop diagram of a system dynamics model, and this may lead to the issue of multi-collinearity in a forecasting equation. This issue will be discussed in the chapter 4.

3.4. Air travel demand characteristics

The link found between consumption and consumer confidence, is leading naturally to air travel demand as air travel spending is part of the consumption picture and in parallel consumption is driven by income and is determining economic growth, a major driver for air traffic development.

Air travel trips for visiting friends and relatives (VFR), vacations, and even business trips can be cancelled or delayed when income is depressed or uncertain. Besides, periods of high economic or political uncertainty are often associated with high volatility of consumer confidence, suggesting that large swings in confidence are also particularly important for air travel demand, as air travel spending for leisure purpose are typical discretionary expenditures. In addition, strong variations in confidence are assumed to be likely driven by major events that are thought to strongly affect household mood, and are often followed by fluctuations in GDP. Therefore they are supposed to determine consumption patterns especially in the occasion of exceptional circumstances.

3.4.1. Propensity to consume air travel and consumer confidence

The personal consumption expenditures as a percentage of disposable income is known as the propensity to consume (Mankiw, 1998) and is a stable ratio for developed countries. As an indicator of the income level, GDP per capita is widely and consistently available. However, it is noteworthy that GDP is intended to be a measure of economic activity, and that is not, strictly speaking, a measure of standard of living. Nevertheless, all other things being equal, it is assumed that standard of living tends to increase when GDP per capita increases, and this makes GDP per capita a good proxy for income.

Propensity to travel by air which measures the average number of air travels per capita per year increases with the income but within a non-linear relationship.

Figure 8 suggests that once real GDP per capita reaches the range of US$ 20 000 to 30 000 the number of trips by air per capita stabilizes. However, what these data do not show is the actual propensity to travel of residents within a country. This would require knowledge of the proportion of travellers at each airport whose complete journeys are originating in that country. It is noteworthy that the relative high score achieved for instance by Mauritius is not just because of its island status but also because it is an attractive destination which generates many inbound passengers. This chart showing the relationship between propensity to travel and GDP per head of population is partly skewed as the number of journeys (using ICAO[12] and OAG[13] data) include all the passengers originating in a particular country which encompasses both residents and non-residents travellers. Therefore the number of journeys per head of capita, shown in the x-axis (exponential rather than linear) is higher than the real one, taking into account that the income shown in the y-axis has been provided by IHS/Global Insight and is representative of the GDP per Capita of the residents in each country.

The BRIC countries (Brazil, Russia, India and China) which are all towards the left bottom end of the curve have been highlighted, showing that these potentially dynamic economies could easily improve their propensity to travel as their economies develop resulting in major increases in air travel demand in these countries.

Although air travel grows linearly with GDP growth, it is still remaining one part of travel growth that is not explained. As part of the consumption picture, income is determining air travel spending level and hence air traffic volume, while in parallel consumer spending is driven by income and by other factors such as consumer confidence. Therefore this index could be a potential indicator for the airline industry development.

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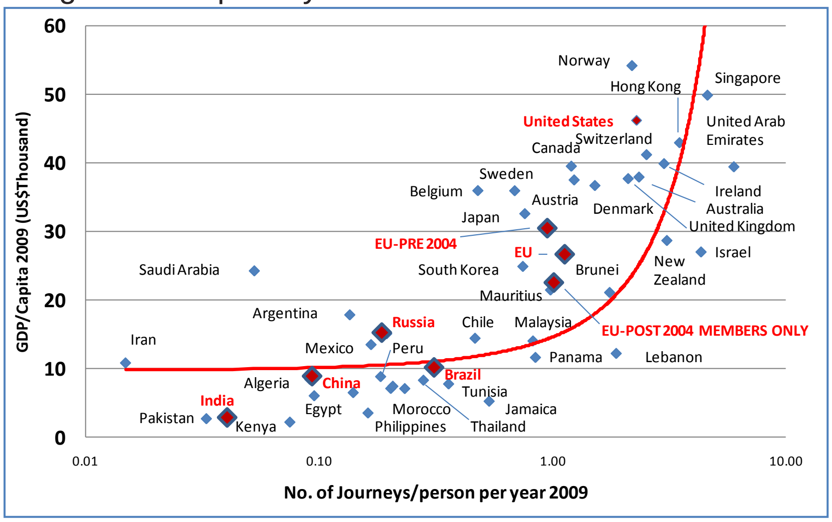
[12] ICAO data as extracted from Forms A that are reported by airlines domiciled in a country

[13] Official Airline Guide (OAG) data have been sorted by number of departures originating from each country in order to supplement the missing data in Form A

Figure 8: Propensity to air travel for selected countries



Source: IHS/ Global Insight, ICAO and OAG

In a study conducted by Pegasus Intellectual Capital Solutions[14] for Northwest Airlines with the objective to have a better understanding of the demand drivers and dynamics of the commercial aviation industry, they applied a multivariate regression and used the industry profitability as their dependant variable, and various economic metrics as their independent variables. They constructed an industry composite income statement starting with 1979, the year the industry was deregulated. Their best regression model used GDP, Consumer Confidence, and a dummy entered in for the years with wars or other external events to estimate the adverse effect on margins of shocks. Redacting the coefficients for the independent variables, the model is shown in equation (2):

Industry Operating Margin = (Coefficient 1)(GDP lagged) + (Coefficient 2)(Consumer Confidence) - (Coefficient 3)(Shock) - .0695 (2)

Their regression on the airline industry indicated that the current operating performance is consistent with the Industry's ever-present dependence on (and vulnerability to) changes in real GDP, Consumer Confidence, and extraordinary events. Due to the extremely good fit of the model (and strong statistical measures), they concluded that this model fairly represented the dependence of the airline industry's profitability (very tightly linked to air travel demand) on the strength of the economy, the mood of consumers and the impact of extraordinary events.

[14] Pegasus Intellectual Capital Solutions LLC is a corporate finance advisory firm www.pegasusics.com/

Among the reasons mentioned to explain why airline profits are volatile, confidence is cited (Morrell and Swan, 2006), as travel demand is sensitive to consumer confidence, which itself is correlated with stock market performance.

However, the possible impact of consumer confidence on air travel growth is still only part of the story, as among the different drivers impacting the growth of an air travel market, factors such as the regulatory framework, the maturity level of a market, urbanization, airlines´ offers, the distribution of the average disposable income among the population (how much money do people have to spend for travelling according to the existing fares and to their income) and jet fuel price are of particular importance.

3.4.2. The regulatory framework

The major forces that are driving airline traffic and enabling to assess whether the patterns of a specific market has changed is linked above all to its regulatory status. Having been one of the most regulated industries in the world, the airline industry has enjoyed increasing levels of liberalization over the past 35 years, beginning in the United States. While the US deregulation took a more "big bang" approach, eliminating all rules at once, EU deregulation took place gradually in three phases, each of them meant to bring the industry one step closer to the single market envisioned by the Single European Act.

The United States and the European Union also approach competition policy differently, with the EU necessarily taking a harder stance on state aid to airlines, as national governments continue to hold substantial stakes in their airlines and therefore take an interest in ensuring the viability of their national champions.

On the other hand, the US has focused more on preventing foreign ownership of airlines, largely to protect the domestic market from foreign competition.

However, as liberalisation both in the US and in the EU civil aviation markets aimed at fostering competition among airlines by removing regulatory constraints on airlines' routes, and on pricing, passengers benefitted from lower fares, higher flight frequency and more routes, leading to a change in air traveller's behaviours with a significant impact on air travel demand modelling.

3.4.3 Fares, market maturity and market typology

There are different levels of segmentation for demand for air travel, as it could be classified either by range, short, medium or long-haul, or by passenger type travelling for business or leisure, or even by flight type operated by network, charter or no-frills carriers.

A key issue in long-term air traffic forecasts is the degree to which a particular market is mature, as time constraints are expected to limit demand for air travel, especially for leisure purpose, translating into a significant fall in annual growth rates overtime.

In the latest UK air traffic forecasts issued in August 2011, the term 'market maturity' is often used to refer to the process by which the demand for a product becomes less responsive to its key drivers over time. It is notably stated that as with most markets, it might be expected that there would be some product cycle in aviation demand, with rapid early demand growth giving way to steadier growth in later years. One explanation mentioned in these forecasts is that, when a good is introduced to the market, it experiences a rapid growth phase as consumers gradually become more aware of it. The growth of demand then gradually slows and becomes less responsive to changes in its key drivers as the product becomes more familiar and widely available. More specifically in the context of the market for leisure air travel, it could be linked to the fact that as the number of flights that people take is increasing, they have less remaining time available for additional trips. This increases the value they place on their remaining leisure time and reduces the likelihood that they will respond to increases in their incomes by increasing their demand for leisure travel. This means that for a constant level of GDP or income growth, the growth in demand for air travel declines over time along with the income elasticity.

According to the Intervistas study published in 2007 , their conclusions show that income elasticity (expressed as the percentage change in demand associated with a 1% change in income) is moving from a low 1.5 for short-haul travels in developed countries to a high 2.7 for ultra-long-haul travels in developing countries. Income elasticity of demand tends to decrease as markets become more mature.

Therefore income elasticity of demand is often used as an indicator of the maturity of a market. Graham, in 2000, for example, suggests the following five-stage model of the market maturation process.

a) 3 earlier stages of market maturity are considered to exist when elasticity values are falling but are still larger than one.:
   i. Stage 1 (Full Immaturity): Constant and substantially greater than 1
   ii. Stage 2: Decreasing but still greater than 1
   iii. Stage 3: Approaching 1

b) Stage 4: Full maturity is defined to occur when the income elasticity is unity or below, that is when increases in income do not produce proportionately larger increases in demand.
c) Stage 5: Full saturation on the other hand is defined to occur when the income elasticity value is zero, meaning that changes in income have no effect on demand.

However there is a need to be careful in assessing that the world air traffic market is maturing, as approaching the unity value in the last 10 years.
As said above, income elasticities are often used to assess the degree of market maturity. In order to assess the progress toward maturity of the world air travel

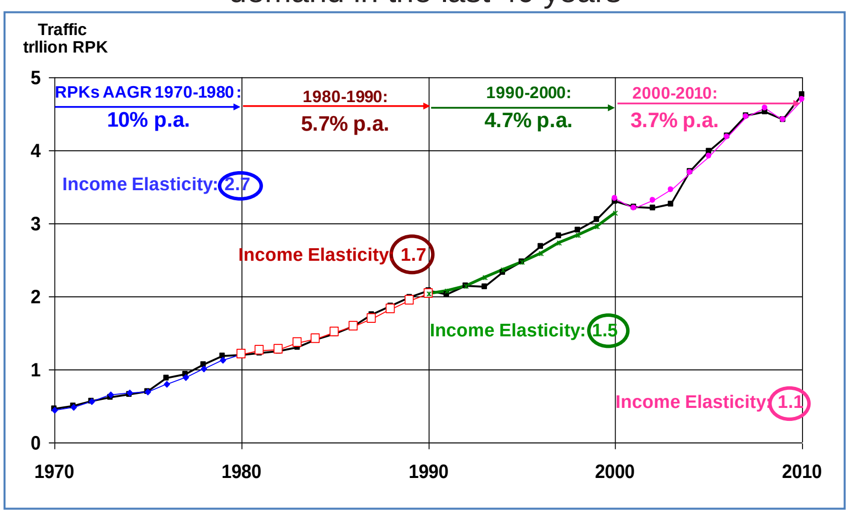
demand, the world traffic expressed in Logarithm of RPKs (Ln(RPK)) has been modeled during the successive decades against the Logarithm of the world real GDP (Ln(GDP)). Through a regression analysis the air traffic has been modelled against only one explanatory variable which is income as measured by Real GDP. The model functional form, as shown in equation (3) has been chosen to be a logarithmic one, in order to be able to measure the average elasticity:

$$Ln\ (RPK) = Ln(k) + \alpha Ln(GDP) \qquad (3)$$

Where k and α are constants, α being a measure of the income elasticity represented by the elasticity of demand to GDP.

The result of this analysis of the world traffic between the successive decades, since 1970 is showing (Figure 9) a spectacular decrease in the income elasticity to GDP.
It confirms that as for all products or services, air travel started its life as highly income elastic. In general, the maturation process is slower for broader categories of products such as air travel which are less subject to changes in fashion, than for more narrowly defined products as for instance package tours.

Figure 9: Models by decade showing declining income elasticity for world air travel demand in the last 40 years



Source: IHS/ Global Insight and ICAO

On the other side, price elasticity is representative of market typology and it is estimated around 1.5 for leisure air travel and between 0.3 and 0.8 for business one (Gillen, Morrison and Stewart. 2003). However, this range of price elasticity tends to be underestimated because it has been calculated largely based on data from the nineties and in today's environment, air travel is likely to be more sensitive to prices.

There are currently good reasons to re-examine empirical estimates of air transport demand income or fare elasticities, deriving from changes in the airline industry itself brought about, among other factors, by liberalization of air transport services in the different regions of the world.

The partial or full removal of restrictions on market access, pricing and capacity prompted the emergence of a multitude of no-frills airlines together with a fundamental restructuring of the business models of the existing full-service airlines. Costs of travel have been driven down, while there have been important developments in the pricing and distribution of air tickets which have resulted in a reduction in input costs and greater fare transparency. Internet has become a vital tool for researching and booking air fares and holidays and has enabled to reach a greater number of potential travelers.

According to a UK CAA (2005) study on the European air travel market, the presence of a no-frills carrier on a route reduces yield by an equivalent to 30% of the mean value of the yield. This is a similar but somewhat lower reduction than the equivalent estimate for the US by Morrison (2002). Morrison found that the presence of a no-frills carrier on a route reduced yield on average by about 38%.

As specified in the UK air traffic forecasts, in principle, market maturity affects the way demand responds to all of its key drivers (e.g. fares) and not just income. In fact, it is standard practice in transport models to assume that travellers' response to fare changes also decreases through time as their incomes increase and they place higher value on the time costs associated with travel.

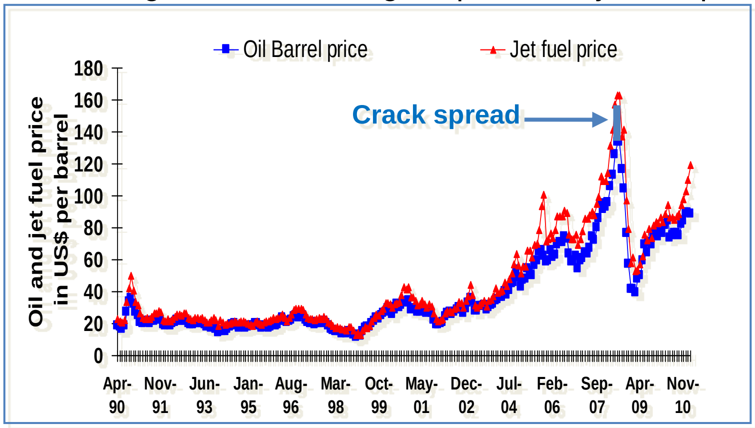
The research indicates that airline demand is becoming less sensitive to income changes and also that the share of income spent on air travel is not showing much growth. Both of these suggest that airline demand may be becoming more mature, with growth being increasingly driven by price reductions rather than income changes.

3.4.5 Oil and jet fuel price: direct and indirect impact on air travel

Jet fuel price is highly correlated to the oil price. For the US air travel market, an adjusted R^2 of 0.96 has been found between World Texas Intermediate (WTI) price and jet fuel price correlation, while for the European one, Brent price and jet fuel price are correlated at 99%. These minor differences in the level of correlation in each regional market are linked notably to the regional differences in the crack spread level. Crack spread, as shown in Figure 10, represents the differential between the price of crude oil and the petroleum products extracted from it. It is the profit margin that an oil refinery is making by "cracking" crude oil which corresponds to breaking its long-chain hydrocarbons into more useful shorter-chain such as aviation fuel.

One of the most important factors affecting the crack spread is the relative proportion of various petroleum products (gasoline, kerosene, diesel, heating oil, aviation fuel, asphalt and others) produced by a refinery. There are regional differences in the value of the crack spread and they are linked to each specific requirement for fuel for heating, cooking or transportation purposes, according to the needs to suit the demand of each local market.

Figure 10: Modeling Oil price and jet fuel price



Source: EIA monthly data for WTI and US Gulf Coast jet fuel price

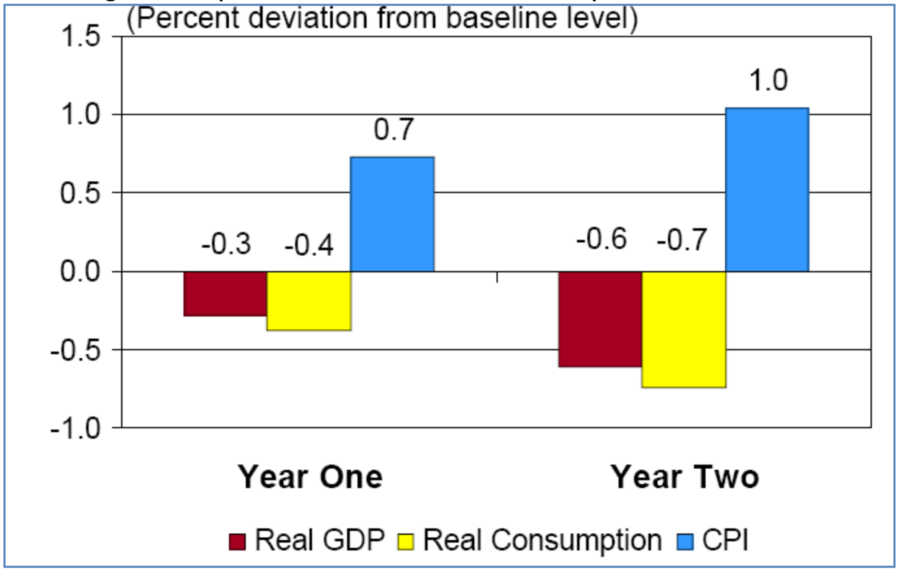
To the air transport industry, oil price in itself is not a determining factor on air travel demand. For instance, the Chief Economist of the International Air Transport Association (IATA), Brian Pearce[15], asserted in an article published by Observer-Reporter in October 2004, that any dampening effect of a high oil price is more likely to come through the impact on economic growth and on consumer confidence. As shown in Figure 11 here below, and in the case of the US market, IHS/Global Insight, a major international economic forecasting company has modelled that when facing a US$10 increase in oil price it impacts the GDP growth forecast by approximately a half percentage point.

During some years of the last decade, the dollar's weakness against the euro has helped cushion European airlines against the high volatility of oil price, traded and billed in dollars, while some legacy US carriers' weak credit ratings prevented them from buying long-term oil futures or other instruments to "hedge" against fuel price increases.

Besides, according to the latest available financial distribution figures (shown in Appendix A) published by ICAO in 2007 on icaodata.com[16], as jet fuel accounts for about 25% of average airline expenses, airlines cannot send back all the jet fuel price increase on airfares, and they are obliged to drive down their other costs while increasing their ancillary revenues.

[15] http://news.google.com/newspapers?nid=2519&dat=20041009&id=rzFkAAAAIBAJ&sjid=_ycMAAAAIBAJ&pg=3130,3386436, accessed in July 2011
[16] http://www.icaodata.com/modules/global/download/FileView.aspx?file=103&section=Scheduled Airlines

Figure 11: Modeling the Impact of a US$10 rise in oil prices on the US economy



Source: IHS/Global Insight

In the event of high fuel price increases, air carriers usually introduce a fuel surcharge to counterbalance any substantial rise in their fuel costs. These surcharges are an amount paid by the passenger, in addition to the quoted air fare, and they can be quite significant, as for instance, during the last oil crisis of the first half of 2008, they were ranging from 10 to 25 % of the usual fare charged by the air carrier. Therefore, it is important to know how these surcharges are shown in the air carriers´ profit and loss statements, and more specifically how they are reported in air carriers financial data, notably when calculating the passenger yield.

The method of accounting as prescribed in national accounting standards vary from State to State. However, internationally adopted accounting standards such as the International Financial Reporting Standards (IFRS) and the U.S. Generally Accepted Accounting Principles (GAAP), require that surcharges should be part of the operating revenues.

Considering the substantial global amounts of these fuel surcharges, internationally adopted accounting standards do not permit the netting of these surcharges with the fuel costs. Hence, the fuel costs have to be reported without being reduced by the corresponding amount of the fuel surcharges, which means that fuel surcharges need to be reflected as operating revenues and not as non-operating revenues. Different methods in accounting or reporting fuel surcharges have the potential to impact passenger yields, especially if these fuel surcharges are reported as non-operating items, or considered as fuel cost reductions or reported separately under other revenues as part of operating revenues.

As per today, there is no clear indication for the carriers on how to report monies collected from fuel surcharges received from the passengers, which means that each carrier is following its own accounting rules. This lack of instruction could affect the traffic forecasts, because it translates into major fluctuations in yields, as it appeared during the 2008 oil crisis, and it could definitely impact the evaluation of price elasticity and hence the air travel demand forecast output.

Considering this potential impact on key indicators, and taking into account that fuel surcharges represent a price adjustment, the International Civil Aviation Organization (ICAO) is still exploring the possibility to recommend that air carriers should include them with passenger revenues, regardless of the fact that they may be accounted for under a special operating revenue account. That’s why the fuel price impact cannot be totally measured through the yield increase and its direct impact cannot be either estimated or modelled.

4. METHODOLOGY

4.1. The method

As discussed in the previous chapters, economic theory maintains that in equilibrium consumers' demand is a function of income and prices of goods. In the past twenty years research on demand for air travel has generated various studies, and among others, Tretheway and Oum (1992) identified the key determinants of airline demand, including price, income, fare of other transportation modes, flight frequency and timing of service, day of the week, season of the year, safety record, demographics, distance, in-flight amenities, customer loyalty and travel time. Theoretically and based on the forecasting technique retained, a comprehensive model would preferably include all the potential explanatory variables, if the size of the available historical time series allows it.

In chapter 2 the available forecasting techniques have been detailed and it was mentioned that the causal models are the most commonly used to forecast air travel demand and as they can relate planning and decision-making variables to forecasts, they can be used to forecast the effects of different policies. These techniques may be applied at the macro-level, to passenger choice modeling, or micro-level. Wickham (1995) provided examples of macro-level forecasts which include projections of total annual domestic traffic and the growth in passenger movements between the US and Europe on a long-term time-span. According to him a passenger choice modeling can be employed to determine whether an individual would choose rail over air transportation, or choose one airline over another, while micro-level forecasting pertains to predicting passenger demand at a more detailed or specific level, such as on a flight, date and fare class basis. Macro-analysis is concerned with system wide air transportation activities and deals with models that are not highly stratified (Bin Alam and Masud Karim, 1998). Macro-analysis of air travel demand is intended for forecasting total activity levels in air transportation and is not concerned with specific city-pair, airline or airport analysis.

4.1.1 Air travel and multiple regressions analyses

At the macro-level of airline forecasting, the principal references are Taneja and Kanafani**.** Taneja (1978) focuses on regression models for aggregate airline traffic forecasting on a regional, national, and international scale. Taneja argues that causal methods, particularly regression, are the most popular methods of forecasting demand for air transportation from a macro analysis point of view. He specifies notably that time series methods cannot, for example, assess the impact of a reduction in fares, the introduction of new aircraft, an economic recession, or the uncertainties associated with the future labour climate.

For Kanafani (1983), aggregate measures of air travel activity such as passenger traffic can be modelled through causal techniques according to

several factors and notably type of service, should it be scheduled airline, charter or commuter aviation.
Causal models are useful if data are available on variables that might affect the situation of interest, while the forecasts produced are more accurate than forecasts derived from extrapolating the dependent variable (Allen and Fildes, 2001).

Regression analyses which are part of the causal models involve estimating the coefficients of a causal model from historical data and it is estimated to be the most reliable method for forecasting air travel demands (Uddin et al, 1986). They are useful in situations with few important variables and many reliable observations that include data in which the causal variables varied independently of one another (Johnston, 1991). Multiple regression methods are designed to account also for variables in non-price factors and can easily be solved using the method of least squares (Draper and Smith, 1981).

In multiple regression analysis, the relationship between air travel demand, the dependent variable and the predictors which are the independent variables takes the form of the following regression equation (4):

$$Y = b_0 + b_1 x_1 + b_2 x_2 \ldots + b_n + e, \qquad (4)$$

where Y is the traffic measured in RPKs, the b_i are the regression coefficients for the corresponding x (independent variables) terms, b_0 is a constant or intercept, and e is the error term reflected in the residuals.
Another commonly used model for demand relationships is the power function. This takes the form of the equation (5):

$$Y = b_0 * b_1 x_1 * b_2 x_2 \ldots * x_n \qquad (5)$$

This model assumes that the marginal effects of each variable on demand are not constant but depend on both the value of the variable and the values of all other variables in the demand function (Moutinho et al, 1998). The parameters of a power function may also be estimated by the method of least squares by first transforming the equation into a linear relationship by using logarithms (Zlatopher, 1984).
Taking the logarithms of the power function gives the equation (6):

$$Log\ Y = log\ b_0 + b_1\ log\ x_1 + b_2\ log\ x_2 + \ldots .. + b_n\ log\ x_n \quad (6)$$

Many empirical studies of air travel demand estimate a linear or log-linear model (Gillen, Morrison and Stewart, 2003).

Although, there is little theoretical basis for choosing among alternative forms of this equation, the log-transformed specification has been largely preferred and employed in previous studies, as in that case, the estimated parameters (b_i) can be easily interpreted as the constant elasticity quotients for those that are meaningful (Bhadra, 2012).

4.1.2 The logarithm functional form

A literature review of a selection of international studies which have used the log functional form in modelling air travel demand is provided here below.

Hollander (1982), in his study of international air travel, has developed models for leisure and business travel with demand equations specified in double-log form. Poole (1988) developed a model to explain changes in the number of visitors arriving in Australia. Separate demand equations for leisure and business visitors were estimated in double-log form for different international air markets, in order to compare airfare, income and exchange rate elasticities.

In 1988, the Australian Bureau of Transport and Communications Economics (BTCE) produced a study of international aviation. The report analysed factors which affect demand for international air services in Australia for five regions of destination. The models used in this study were based on a single equation double-log relationship, with demand expressed as a function of real income, real airfares and relative prices. In 1992, the Australian Bureau of Tourism Research (BTR**)** used a dynamic model of travel behaviour which includes lagged variables to forecast the number of visitors to Australia between 1992 and 2001. A double-log equation was specified with the number of travellers assumed to be a function of income and relative prices.

Nevertheless, Oum et al (1992) established a list of pitfalls that could occur when demand models are estimated and hence may affect the interpretation of the elasticity estimates from some empirical studies. They mentioned that as most studies of air travel demand use either a linear, log-linear or double-log functional specification, elasticity estimates can vary widely depending on the functional form. Therefore, the choice of functional form should be selected on the basis of statistical testing not ease of interpretation.

Considering the aggregated structure of data and the objectives settled in the first chapter of this thesis, the macro-analysis approach seems to be most appropriate for the three case studies. Indeed, the markets that are targeted for this thesis, are all quantified by aggregated data on the traffic side but also on the explanatory variables to be used. The multiple regression method under a double-log specification has been preferred for modeling purposes.

4.1.3 The Ordinary Least Square method

Most of the previous studies related to air travel demand have adopted a standard multivariate linear regression approach by using ordinary least squares (OLS) method to estimate the parameters (Anderson et al, 2002; Black, 1992; Borenstein, 1989; Evans and Kessides, 1993).

This method derives its name from the criterion used to draw the best-fit regression line: a line such that the sum of the squared deviations of the distances of all the points to the line is minimized. OLS (also called Linear Regression) uses the method of least squares to estimate the "best fit" of a set of independent (X) variables against the dependent variable (Y) variable expected to be explained or predicted. The primary product of regression analysis is a mathematical equation which can be used to predict values of the dependent variable, given the values of the independent variables. Also associated with regression are measures of precision and accuracy, commonly referred to hypothesis tests. The OLS method is based upon a number of statistical assumptions such as, the model is linear in its parameters, the residuals (errors) are homoscedastic (reflect constant variance), they are not correlated with one another over time, the independent variables and the residuals from the model are uncorrelated and the data are derived from a normally distributed population.

In addition, taking logs is another way in which heteroscedasticity can be removed, since this transformation reduces the variation in the variables. It is a simple and practical measure to cure most heteroscedasticity problems.

An extension to the OLS method, the stepwise regression technique has been widely used in air travel demand forecast.

When studying econometric analysis of international air travel demand in Saudi Arabia Abed, Abdullah, Ba-Fail and Jasimuddin (2001) used stepwise regression technique in order to determine from a list of variables the most suitable ones to represent the demand for international air travel in Saudi Arabia. Among a list of 16 potential explanatory variables, total expenditures and population size were found (under the stepwise approach) to provide the most appropriate model to represent this specific demand. Rengaraju and Arasan (1986) developed regression models for determining air travel demand in 40 city pairs in India by using stepwise multiple linear regression in their analysis. In 1998, Bin Alam and Masud Karim modelled demand for air transportation in Bangladesh by using a stepwise multiple regression method and as did Aderamo (2010) when assessing the demand for domestic air transport in Nigeria.

This technique allows to choose a model by deciding whether the inclusion or exclusion of an extra variable significantly improves the model. It looks for the best combination of independent variables that can explain the variation in a dependent variable. A unique advantage of the stepwise regression analysis is its ability to re-examine at every step of the computation, the independent variables incorporated into the model in the previous steps (Hauser, 1974).

This approach begins by including a variable that gives the best fit in terms of explaining the response in a simple linear regression. The next variables are added one by one to the model, and the F-statistic for the variable to be added must be significant at the defined level, in order to improve the existing model, the greatest contributor to the total variance being entered first. The used criterion for adding or deleting explanatory variables in a stepwise regression is based on the *partial F-statistic*, which derives from the F-statistic.

This statistical method enables to select the most significant independent variables from any given set of variables (Draper and Smith, 1981).

After a variable is added, the stepwise method looks at all the variables already included in the model and deletes any variable that does not produce an F value which is statistically significant. Once this check is made and the necessary deletions accomplished, then another variable may be added to the model. When using this technique it is possible for a variable to enter the model, later leave it, and then possibly re-enter the model to stay. If the model can be improved, the variable is deleted and the stepwise procedure repeated until no further variables are either included or deleted.

The stepwise process ends when every variable in the model is significant (based on the F statistical value) and none of the variables outside the model is significant.

However, the stepwise process is only a technique and there is a need to feed the software with a selection of regressors that have been identified as being potential drivers of air travel demand.

4.2. The determinants of air travel demand

As indicated previously**,** air travel is generally undertaken for two main reasons: leisure (including VFR) and business. Leisure travellers, as consumers, aim to maximise the utility, or satisfaction, derived from air travel the associated consumption of holiday experiences. On the other hand, business travellers, who use travel as an input to final production, are interested in minimising costs for a given level of output. Therefore leisure and business travellers are likely to respond differently to changes in certain socioeconomic factors influencing demand and ideally (when respective data are available), should be modelled separately.

4.2.1 The potential regressors

a) Economic activity

The level of economic activity, usually measured by GDP, at the country of departure has been found as an important determinant of air travel demand (Mitchell, 1993 and Hooper, 1993). Although GDP does not specifically measure income distribution, high levels of GDP are generally associated with high levels of disposable income. As air travel spending for leisure purposes is generally regarded as discretionary expenditure, the demand is expected to be elastic with respect to income. Tretheway and Oum (1992) noted that air travel exhibits cyclical behaviour and that very few goods are as responsive to income as air transport. Positive correlation capture the essential responsiveness of passenger demand to changes in economic growth, such as GDP and/or personal income (Bhadra, 2003) and (Bhadra and Kee, 2008). Therefore air travel demand is likely to be sensitive to changes in economic conditions which might affect income.
For international air travel, the level of trade is supposed to be a driver for the business travel segment (Gillen, 2009). However trade (imports or exports) cannot be used in the same modelling equation that GDP or income as they are strongly correlated, due to the fact that GDP calculation encloses trade values.

b) Travel price

Airfares form a large proportion of total travel costs for leisure traveller and are one of the most important determinants of leisure travel demand. Dresner (2006) and Graham and Shaw (2008) show that there exists a negative elasticity between ticket prices and air traffic: the higher ticket prices, the lower the demand for flights.
Studies of domestic aviation in Canada, Oum and Gillen (1982) and Oum, Gillen and Noble (1986) found also that a decrease in the cost of air transport would, lead to a more than proportionate increase in the demand for air travel. However, the elasticity of business demand with respect to airfares is likely to be lower than the one for leisure travellers.

In addition to the air fares, the cost of living at the travel destination is also part of the total travel price and is taken into account by the leisure travellers, as they may choose to spend their holiday at home (or consume alternative discretionary goods and services at home) if tourism prices in a destination country are higher than tourism prices in the home country.
In that context, the use of consumer price index (CPI) and nominal exchange rates can be significantly used in modelling international air travel demand (Witt and Martin, 1987), as in combination they provide the real exchange rates which enable the comparison of relative prices between countries.
Therefore the real exchange rate measures relative purchasing power, it could also explain how a leisure air traveller could substitute foreign to domestic holidays (and vice-versa), as well as switch between different potential foreign destinations. In addition to its link to the leisure segment of air travel demand, the real exchange rate may also influence the flow of imports and exports. An increase in the real exchange rate reduces the relative price of goods imported into , but results in an increase in the price of its exports relative to other countries. Hence, a fall in the price of imported goods in a country might lead to an increase in business travel of the exporters of these goods.

c) Quality of service

Generally service quality attributes are not significant determinants of air travel demand for leisure purposes, although an airline´s safety and security record (Morrison and Winston, 1989) may be important in determining airline choice. However, quality of service, particularly flight frequency (Ippolito, 1981) has been found to be of some importance to business travellers (Morrison and Winston, 1985). If an increase in flight frequency and/or total available seats can reduce time delays for consumers then demand for air travel on a particular route may increase. According to Tretheway and Oum (1992), the most important qualities of service elements in air travel demand are service frequency and convenience.

d) Substitute destinations

As international air travellers may choose among a range of competing or substitute destinations, modelling air travel demand should consider potential substitute destinations by including the price of travel between the originating country and the possible destinations. Although this analysis has some theoretical appeal, it is often unattractive in practice because of the difficulty of identifying alternative destinations as this a very subjective process. In addition this would require the collection of substantial amounts of data. As a consequence, many studies on air travel demand exclude price variables for substitute destinations.

e) Intermodal competition

In the United States for short-haul travel the car may be a close substitute, while in Europe high-speed train may be a close substitute (BTCE, 1994) for both short and medium haul. Generally for long haul international travel such as the US-EU travel market, the best mode is air. In that case, the cost and quality of alternative transport modes will therefore have negligible impact on air travel demand.

f) Population and distance

The populations of origin and destination cities (or countries) and the distances between the cities are determinants often considered in gravity specifications of transport demand. In economic terms, population can be thought of as a proxy for the size of the market between two cities. Any increase in the size of the market has the potential to increase demand for travel between the two cities. Distance can affect a traveller's choice of destination in terms of the cost of travel and the time taken to reach the destination. Thus an inverse relationship between distance and demand for travel would be expected.

g) Marketing

Marketing expenditure by major airlines which promote holiday destinations and customised holiday packages i s a potential determinant of air travel demand. Crouch, Schultz and Valerio (1992) reported a regression analysis of demand for international tourism to Australia which employs traditional variables such as price and income, but also includes the level of marketing activity. They found that the marketing activity was statistically significant in explaining the variation in air travel demand to Australia from various countries.

h) Migration

Past migration patterns may have also an impact on demand for air travel, as VFR is an important part of leisure travel. Travel demand is expected to be positively related to the number of residents in a country and born overseas.

i) External factors

An increase in the amount of leisure time available to consumers may increase the demand for overseas holidays. Duffey (1992), reporting on structural change in the US domestic airline industry suggested the possibility that such forces as the trend toward a shorter working week and the shifting age composition of the population may significantly accelerate the growth rate of air transport.

Besides demand for air travel is influenced by seasonal factors (northern and southern summers), special events such as the Olympic games (for both domestic and international travel) and by crises such as SARS as well as political unrest such as the Arab Spring.

Additional qualitative factors such as individual tastes and preferences are also important for air travel demand but they are by essence difficult to quantify.

4.2.2 The explanatory variables retained for the three case studies

In air travel, ideally, market segment boundaries should be defined by first separating leisure and business passengers (Gillen, Morrison and Stewart, 2003). However, in the three case studies analyzed in chapters 5, 6 and 7 respectively, forecast of air travel demand is based on total travel by air in each specific market. Business and pleasure travel are not separated due to the lack of adequate statistics preventing in depth separate analyses of business and leisure air travel demand. Besides, the objective is to produce a macro-model and not individual city-pair analysis. Some Origin-Destination (OD) markets are heavily business-oriented, others are leisure oriented, but most are a mixture of both types of travel, as it is pictured in each of the three aggregated markets studied.

a) Economic activity

The discretionary income is that portion of disposable income in excess of the amount necessary to maintain a defined or historical standard of living. This last type of income may be saved or spent with no immediate impairment of living standards. Thus it would appear that discretionary income would be a better and more consistent predictor of air travel than either disposable or national income. However, It is difficult to quantify the discretionary income and to obtain similar consistent data series on discretionary income for both the US and the EU.

Besides, It appears that business travel is not sensitive to personal income (Taneja, 1971). Business travel seems to depend, among other things, on GDP and particularly on exports and imports (part of the GDP). Furthermore It has been stated previously that the level of income is an explanatory variable which partially indicates the growth of the air travel demand for leisure purposes. Based on the above, it has been decided that the economic activity is represented by GDP and income in the three case studies.

The way income is represented in demand studies may be important. Alperovich and Machnes (1994) argue that the use of current income is at odds with economic theory which suggests that permanent rather than current income is the relevant explanatory variable that determines demand. They suggest there may be a role for wealth in models of air travel demand, as air travel by employed persons is likely to be related to changes in disposable income, while air travel by retirees may depend on both wealth and retirement income. When reviewing several empirical studies on air travel demand modelling, Bhadra (2012) concluded that no consideration was given to wealth

or permanent income as opposed to or in addition to current income determining air travel.
Examining co-movement data for the period 1970-2002, CAA (2005) concluded that "(correlations) suggest that household wealth may be an important predictor of demand for air travel over the short term´´. This may in part be explained by the fact that changes in consumer confidence are closely related to wealth since consumers are known to use asset, and in particular house prices as an indication of the state of the economy. CAA thus used house prices, in addition to consumer expenditure, air fares, and effective price of tourism, to model and forecast international air passenger traffic for a given market in a particular year.

For the three case studies, the variables taken into account as potential explanatory variables of the economic activity are both real GDP (RGDP) and income (RGDP/Cap) expressed in GDP per Capita in real value, as representative of the current household income. For the third case study, real trade values (Real Imports and Real Exports) are also introduced in the stepwise regression. In addition and in order to try to capture the wealth effect, rate of unemployment (as easily available in terms of forecasts in all of the travel markets considered) as well as consumer confidence indices (CSI or CCI) are also considered as potential explanatory variables.

b) Travel Price

Leisure travel is generally regarded as discretionary expenditure. Many goods services compete with leisure travel for a share of the consumer's discretionary budget. Because of the existence of many substitutes, passengers travelling for leisure purposes tend to be sensitive to changes in airfares. More particularly, Dresner (2006) indicates that leisure passengers display higher elasticities of demand and lower valuations for travel time compared to business travelers. When looking at the total cost of travel, business travellers seem to be less responsive to changes in airfares, as the time component (part of the total cost of travel) is more valuable for them than for the leisure travellers and hence airfares form a smaller part of their total travel costs. However measuring the cost (or price) of tourism is difficult (Morley, 1995**)** and researchers will often choose the consumer and retail price. In the three case studies the total cost of travel are represented by the level of air fares and by CPI and exchange rates when applicable.

It is noteworthy that it is difficult to obtain valuable fare series for some markets and yield is taken as a proxy for the ticket price. Yield is defined as revenue per RPK, and to compute yield the accounting procedure is to divide the total passenger revenue for a given time in a given market by the total RPKs in that time period. The real measures of yields are calculated by applying the inflation rate through the CPI measure.

For the three case studies, the other variables taken into account as potential explanatory variables are both real fares (RFares) values (when available), real values of yields (Ryields), CPI and Exchange Rates (for the international segment).

c) Quality of service

Tretheway and Oum (1992) explain that two of the greatest lessons learned from airline deregulation in North America were that discounted airfares induce consumers to travel more often and that they opened a whole new market segment for air travel demand. According to Graham and Shaw (2008), the escalating desire and propensity to fly is driven by the growing affordability of air travel, which stems from increased disposable income and the growth of LCCs, offering lower fares.

Assuming that the LCCs and the charters (in Europe) are providing a lower or different quality of service, air travel demand is modelled according to the category of carriers for the three case studies.

Therefore the quality of service is broadly taken into account, notwithstanding the frequencies and convenience factors (not available in the context of this thesis which is studying aggregated markets) that are supposed to be embedded in the modelling of the traffic carried by each category of carriers.

d) Other potential factors

Reviewing 23 key empirical studies covering the last quarter century, InterVistas (2007) concluded that the changes in air fares are the key factor in determining air travel demand responses. The exact magnitude of the demand responses depends upon types of passengers (i.e. business vs. leisure passengers), distance of travel (short-haul vs. long-haul travel), carrier vs. market level responsiveness in demand changes (i.e., differentiated responses in traffic with respect to fares) and income elasticities.

The choice of potential regressors chosen for the three case studies are in line with the findings of the empirical studies reviewed by the InterVistas study.

Regarding other potential explanatory variables as described in section 4.2.1, there were either no data available to represent the substitutes, the population and distances, the migration patterns, the marketing effect, the intermodal competition, the external factors or no possibility to integrate them in the context of aggregated data as decided for the scope of this thesis.

4.2.3 The data set used and associated limitations

The data used for this analysis were obtained from several different sources. In this section, the sources of each variable are described in detail and several data related issues are discussed.

a) Traffic and yields

The dependent variable, time series of the number of RPKs carried in each market is taken as follows:

i) For the Domestic US market from the Bureau of Transportation Statistics (BTS) which publishes monthly passenger traffic data reflecting 100% of scheduled operations for U.S. airlines reporting "T-

100 Market"[17] data. This database is frequently used by the aviation industry and the time series data are available from 1980 to 2010. Based on the segmentation described in Chapter 5, the traffic of the legacy carriers and LCCs have been obtained from ICAO. This UN specialized agency provides a comprehensive air traffic database for international and domestic segments (both for scheduled and non-scheduled flights). The database can be accessed at icaodata.com and contains, on an annual basis, operational, traffic, capacity and financial statistics of scheduled airlines, as well as of non-scheduled operators. The main interest of this database consists in providing data by country, and not by pre-aggregated regions, as well as by city-pairs. Within the database by country, statistics are provided for airlines registered in a given country on a yearly basis. Unless otherwise indicated, all descriptive statistics presented are valid during 1985–2010. Yield series have been extracted for the whole US Domestic market from the Airlines For America[18] (A4A) site, and for each type of carriers considered in the supply side segmentation from the ICAO database.

j) For the European market from various data sources including, ICAO, IATA, Official Airline Guide (OAG), Association of European Airlines (AEA), European Regional Airlines Association (ERAA), the airlines annual reports and Ecole Nationale de l´Aviation Civile (ENAC). The global Domestic and Intra-States traffic registered between city-pairs part of the EU 15 geographical definition has been extracted from the ICAO database reported in the Forms A (monthly reporting), ´´Traffic for Commercial air carriers´´ (for estimation of the Domestic traffic of each State), B (monthly reporting for both domestic and international segments) ´´On-Flight Origin and Destination´´ (OFOD) and C ´´Traffic by Flight Stage´´ (annual reporting for international segments) (TFS).
In that context it is necessary to point out some issues that are linked to these data collections hence explaining why there was a need to supplement these data by other sources.
Both Forms B and C report passengers number and therefore the great circle distance (GCD)[19] has been calculated for each city-pair and multiplied by the number of passengers in order to get the corresponding RPKs.
It is worthwhile mentioning also that OFOD data do not represent true origin and destination data. They only identify the origin and destination of a passenger or shipment (of freight and mail) as is presented in each portion of the travel document. In the case of passengers, it represents the origin and destination associated with each flight coupon present in the ticket. However, it is not possible to link these coupons together to arrive at an itinerary, consequently, as far as the statistics are concerned, each coupon represents a new passenger and the true origin

[17] T-100 Domestic Market (All Carriers) database of the Air Carrier Statistics (Form 41 Traffic) available at http://www.transtats.bts.gov/.
[18] A4A: formerly known as Air Transport Association (ATA)
[19] GCD formulae=60*(180/PI())*(ACOS((SIN(N48)*SIN(Q48))+(COS(N48)*COS(Q48)*COS(O48-R48)))*1.8531)

and destination of the journey is lost. For instance a passenger flying on a Lufthansa flight between Berlin and Paris and then connecting to an Air France flight between Paris and New York will counted twice, and will be added to the Intra-EU market as well as to the EU-US one. Hence the OFOD data represents merely the origin and destination of passengers on direct flights. These data are useful to compare current market shares and operations, but are not helpful to identify potential markets currently only accessible through connecting flights.

Traffic statistics by (international scheduled) flight stage for each airline providing international scheduled air services are collected annually on Form C. For ICAO the definition of ´´international´´ is based on the notion of a flight stage[20] which is classified as either international[21] or domestic[22]. Flight stages between a State and territories belonging to it, as well as any flight stages between two such territories, should be classified as domestic. This applies even though a stage may cross international waters or over the territory of another State. In the case of multinational air carriers owned by partner States, traffic within each partner State is shown separately as domestic and all other traffic as international.

It is noteworthy that “Foreign” cabotage traffic (i.e. traffic carried between city-pairs in a State other than the one where the reporting carrier has its principal place of business) is shown as international traffic In the context of the European air travel market which includes both Domestic and Intra-Europe flights, cabotage has been allowed in the countries which form the EU since 1 April 1997. At that time there was no indication what the impact of the new rules would have on the domestic services of the member countries and therefore cabotage traffic is reported as “international”. In the mean time, LCCs such as Air Berlin, Easyjet or Ryanair, have entered the domestic market of other major States (apart from their State of domiciliation) in the EU. According to data derived from the schedules for these three LCCs, as shown in the OAG, it is estimated that in 2010, about 10 per cent of their seats on international services were offered by these three carriers for cabotage flight operated in France, Germany (excluding Air Berlin), Italy, Portugal, Spain, and the United Kingdom (excluding Easyjet). This issue of cabotage services is distorting the share between the international and domestic traffic in the EU area which in turn would distort any future traffic forecasts specific to each market. There exists however one limitation with the use of such data for international air traffic. Due to a lack of knowledge of some reporting entities, some of the cabotage traffic is reported in the Form A under domestic traffic while it is not

[20] A flight stage is the operation of an aircraft from take-off to its next landing.
[21] **International**. A flight stage with one or both terminals in the territory of a State, other than the State in which the air carrier has its principal place of business.
[22] **Domestic.** A flight stage not classifiable as international. Domestic flight stages include all flight stages flown between points within the domestic boundaries of a State by an air carrier whose principal place of business is in that State.

reported in Forms B or C, as an Intra-Europe traffic, while some time not reported at all.
However, for this case study as it is related to the sum of the Domestic and Intra market segments, this has no major implication except that the total market may be over or under estimated. Besides, as both OFOD and TFS published by ICAO are not achieving a complete geographical coverage, it was necessary to supplement with additional sources such as ENAC which gathers city-pairs data from each national aviation authorities. To avoid difficulties arising from differences between the data sources, only one source is used on any particular traffic sub-market. For instance when data is provided by both the UK and the French CAAs on all the city-pairs linking these two countries only the data provided by the French CAA are aggregated.
In a very few cases where no data are otherwise available for a particular traffic flow, estimation of actual traffic (only for scheduled) has been extracted from OAG in terms of ASKs, corrected with assumptions about average load factors. For the non-scheduled traffic it has been consolidated through traffic data provided by ICAO, IATA and ENAC. For the traffic related to network carriers, consolidated with the traffic reported by the regional carriers linked to them, data have been extracted from AEA Summary of Traffic and Annual Results (STAR) report which provides passenger and cargo data by airline and by reported geographical region (domestic and intra-Europe) as well as aggregate yield revenue information., as well as ERAA statistics available on their site.
Yield series have been extracted for the whole EU market from the financial forms of ICAO, for the network carriers from the AEA STAR[23] and for the non-scheduled carriers and LCCs from the ICAO database, as reported in the financial forms EF. Then to reflect real values the yield are deflated with the inflation index.

k) For the EU-US air travel market traffic data are extracted mainly from the ICAO site, supplemented by various data sources including, OAG and ENAC. The global Domestic and Intra-States traffic registered between city-pairs part of the EU 15 geographical definition has been extracted from the ICAO database reported in the Forms C. Traffic flows data by city-pair have been extracted from the ICAO database, before being aggregated at a EU country to US and then consolidate to reflect the global traffic between USA and the EU 15 States.
In that context it is necessary to point out some issues that are linked to these data collections hence explaining why there was a need to supplement these data by other sources. It is noteworthy that both forms report passengers number necessitating additional computation (cf above the comments made for the data set used for the EU market)

[23] Real Yields: AEA is adjusting the current yields for exchange rate fluctuations and inflation. The constant revenues are calculated to reflect the exchange rate effect by using OECD Exchange Rates (for a basket of carriers). Then these constant revenues are deflated based on OECD Consumer Price Indices (for the same basket of countries than above) and are then aggregated and used to calculate a general index which is applied to the initial current yields.

to get RPKs. In particular, the usefulness of the ICAO database is limited by the fact that the data represent only scheduled passengers carried on airlines domiciled in a country, and the data between countries vary in quality due to reporting issues.
Data filed on the Form C represent, on average, some 85% of international RPKs world-wide, hence not achieving a complete geographical coverage. Therefore, it was necessary to supplement with additional sources such as ENAC which gathers city-pairs traffic data (scheduled and non-scheduled) from other sources. In a very few cases where no data are otherwise available for a particular traffic flow, estimation of actual traffic (only for scheduled) has been extracted from OAG in terms of ASKs, corrected with assumptions about average load factors. For the network carriers traffic and the non-scheduled traffic it has been consolidated through traffic data provided by ICAO, Form 41, AEA and ENAC.
However, the data reported from AEA (scheduled traffic for European air carriers) on the North Atlantic route are including any scheduled service between Europe and North, Central or South America via gateways in continental USA (including Alaska and Hawaii) and Canada. Therefore it is overestimating the European network traffic. From Form 41, the scheduled traffic for the US network carriers has been extracted on the Atlantic segment. The sum of the EU and US network traffic provides the scheduled traffic for the network segment on the EU-US air travel market. The difference between the whole EU-US air travel market and the network traffic segment gives the non-scheduled traffic.
Yield series have been extracted for the US carriers traffic on the Atlantic segment from Form41, while the ones for the EU carriers have been extracted from the AEA STAR for the North Atlantic segment.

b) The economic factors

The economic factors used as explanatory variables in this analysis, namely GDP, income, trade, rate of unemployment, CPI, exchange rates (as easily available in terms of forecasts in all of the travel markets considered) as well as consumer confidence indices (CSI or CCI) are provided by IHS/Global Insight (both in historical and forecast values) for US and Europe. However for Europe the EU CCI is extracted from the Business Surveys Unit of the European Commission[24].

4.3. The process

4.3.1 The analysis rationale

In general, the research that have examined whether indexes of consumer confidence help to model and forecast air travel spending were based on both latest available data, the data available to the researcher, and data that were available to forecasters in real time.

[24] **ec**.europa.eu/economy_finance/publications/publication7568_en.pdf

For the purpose of this thesis, and in the context of forecasting air travel demand, real-time macroeconomic data, as opposed to the data available in today's data bank are needed, as the aim is to investigate whether consumer confidence could help in forecasting traffic more accurately during period of uncertainty.

As a result, the regression exercises and forecasts that are contained in this research are indicative of the value of the consumer confidence indexes in both modeling and actual forecasting.

For each step of the experimental tests for each case study, a similar approach is followed along the procedure described here below.

4.3.2 The monthly analysis: the Box-Jenkins´ steps and technique

As a preliminary step the consumer confidence indices will be tested as sole explanatory variables introduced in a time series analysis based on monthly or quarterly traffic data. By using real-time data with a sample period of Y1M1 to YnM12, the forecasting equation is estimated to generate a forecast for Yn+1M1. Then the same process is done by including the consumer confidence index. The number of lags of variable should remain between 1 and 4 which is fairly typical with monthly or quarterly data.
This recursive forecasting procedure is repeated until the sample is exhausted, so the final forecasts are for 2010 M12, based on data from Y1M1 to 2000M12 or from Y1M1 to 2007M12.
The aim is to compare the out of sample forecasts to the relevant actual values during crises times such as 2001 to 2003, or 2008 and 2009.

At this stage it is important to choose a class of time series models with which to work. As discussed in Chapter 2, there are two basic approaches for modeling, either by developing a causal model or a purely stochastic (time series) one. Intermediate between the two models is the class of stochastic-dynamic models, which contain both causal components and nontrivial stochastic components. When analyzing the short-term behavior of a process, the Box-Jenkins model can be used in both stochastic or combined stochastic-dynamic models. In that context, the behavior of the endogenous variable is related not only to its past behavior, but also to the behavior of exogenous variables as well. Therefore, the current behavior of the variable of primary interest may be related to the past behavior of the exogenous variable which is called a *leading indicator* (Brockwell and Davis, 2002). Obviously, if there is a strong lagged relationship between an exogenous variable and the variable of primary interest, the precision of the forecasts will be considerably enhanced. Since the model class is expanded, the precision of the forecast may be increased over that corresponding to the pure stochastic model.

The BJ modelling procedure allows statistical analysis of time series through Auto Regressive Moving Average (ARMA) or ARIMA (I for Integrated) models. It is useful as it may be performed without the need of an economic theory behind, especially if the analysis is aimed to short period forecast and when there is not *a priori* information on the link between the dependent and the explanatory variables. It enables also to model a time series with seasonal components (Anderson 1976). BJ is used in this thesis for the monthly analysis of the data.

The main assumption behind a BJ model is that the time series is stationary which means it has a constant mean, a constant variance and a constant auto-correlation structure. When series are seasonal, there is a need to apply long-term differencing in order to achieve stationarity in the mean, as modelling with non-stationary variables leads to spurious correlation. In addition when the dependent and the explanatory variables show seasonal variation and that they are seasonally integrated at the same frequency, then the probability to derive spurious relations could be very high (Abeysinghe, 1991) and increasing with the sample size.

Although there are two types of BJ models, the seasonal and the non-seasonal ones, the seasonal ones are only used to describe a time series that exhibits seasonal fluctuations but does not contain a trend component, reflecting that this time series is non-stationary by reason of seasonal effects only. On the other hand, the non-seasonal BJ models are used to model stationary time series. This implies that a time series that exhibits a combination of trend, seasonal and cyclical fluctuations must be transformed (Granger and Newbold, 1974) into a stationary time series before any of the non-seasonal BJ models can be applied to the transformed series. It is also possible that a series may not exhibit any of these components but the level of the fluctuations about the mean or about a fixed level is not constant, then the time series must be transformed in order to stabilize variance before applying the model.

This modelling procedure involves an iterative three-stage process of model selection, parameter estimation and model checking. Recent explanations of the process (e.g. Makridakis, Wheelwright and Hyndman, 1998) often add a preliminary stage of data preparation and a final stage of model application (or forecasting). For each step of the procedure, there are specific tests to perform.

The first step is data preparation and it involves transformations such as square roots or logarithms. Transformations of the data can help stabilize the variance in a series where the variation changes with the level typical of economic data. The input data must be adjusted to form a stationary series, one whose values vary more or less uniformly about a fixed level over time. Then the data are differenced until there are no obvious patterns such as trend or seasonality left in the data. “Differencing” means taking the difference between consecutive observations, or between observations a year apart. The differenced data are often easier to model than the original data.

Then, an Augmented Dickey-Fuller (ADF) unit root test with intercept and trend has to be carried out in order to check the stationary or not of the data series. The ADF test has a negative number. The more negative it is, the stronger is the rejection of the hypothesis that there is a unit root at some level of confidence. As mentioned in the Chapter 2, the unit root testing technique is used to identify if two time series have stable long-run relationships with one another as opposed to spurious regression. The intent is to determine if they are co-integrated, and the preliminary requirement to use this procedure is to check if these variables are stationary. The possible presence of co-integration must be taken into account when testing hypotheses concerning the relationship between two variables having unit roots (i.e. integrated of at least order one). The usual procedure for testing hypotheses concerning the relationship between non-stationary variables is to run OLS regressions (providing correlation information and not necessarily causality) on data which had initially been differenced.

Although this method is correct in large samples, co-integration provides more powerful tool when the data sets are of limited length, as most economic time-series are. Testing the hypothesis that there is a statistically significant connection between two time series is done by testing for the existence of a co-integrated combination of the two series. If two time series are co-integrated, a linear combination of them must be stationary. Therefore this combination needs to be tested for stationarity by first estimating it (through OLS) and then running a stationarity test on the estimated linear combination series. This is the Engle-Granger two-step method. The Granger causality test is a statistical hypothesis test for determining whether a time series is useful in forecasting another, beyond the correlation link reflected in regressions .

The Granger causality test statistic is a F-statistic testing the hypothesis that the coefficients on all the values of one of the variables included into the model are zero.

In order to test the efficacy of the various models that can be produced by the BJ procedure, two tests are used, namely, the Root Mean Square (RMS) per cent error and Theil's *U* test.

The RMS per cent error should be as low as possible, while *U* always ranges between 0 and 1. A zero value indicates a perfect fit, and a value of 1 for *U* implies that the predictive performance of the model is as bad as it possibly could be.

There is also a need to test the residuals of the estimated model and analyse the relative correlogram, in order to estimate if the residuals are white noise. In that case, the model is correctly specified as they are homoscedastic and non-correlated. if they are not white noise, the analysis of their correlogram gives indications of how to modify the model initially defined.

The second step is related to the model selection**,** as the BJ framework uses various graphs based on the transformed and differenced data to try to identify potential ARIMA processes which might provide a good fit to the data analyzed. Later developments have led to other model selection tools such as Akaike’s Information Criterion which will be described in section 4.5.

The third step, the parameter estimation, is done through software computations and enables to find the values of the model coefficients which provide the best fit to the data.

The fourth step, model checking, involves testing the assumptions of the model to identify any areas where the model is inadequate. If the model is found to be inadequate, it is necessary to go back to the second step and try to identify a better model.

The ARIMA approach allows to think about the data and may be used as preliminary analysis before applying a multivariate analysis on a yearly basis, as it is done for the case studies analyzed in this thesis.

4.3.3 The annual analysis: the OLS steps

For each market, there are strong evidences that the way, airfares and income are impacting traffic growth, has developed a pattern which is no more the same before and after the year of the liberalization of any air travel market. This is the reason why for an increased forecasting accuracy, the historical data series to be modelled are starting from an estimated date assumed to have produced a stabilised traffic growth scheme.

For the annual analysis, the first step is to produce a forecasting equation that does not include a consumer confidence index as a right hand side variable, by modeling the traffic successively until 2001, 2002 and repeatedly until 2010. Using the baseline equation, a series of forecasts are generated, just as if those forecasts are made in real time. To each date for which a forecast is issued, the exact data set available to a forecaster in real time have been made available. The set of forecasts are made in a recursive fashion and then the forecast errors are calculated.

Then, it is tested if the forecasting equation is modified by adding an index of consumer confidence in the parameters to be considered by the stepwise exercise and the forecast exercise is reiterated. The model including the consumer confidence index (if applicable) is compared to the previous one by calculating the increment to the goodness of fit of the model and by looking at the change in significance statistics tests resulting from the addition of the confidence indices to the equation. If the confidence index has appeared as significant enough to enter the forecasting equation, the forecast error is evaluated to check if it has decreased significantly from the addition of the confidence index in the regression.

The estimated results based on economic forecast known at each period are then plotted to be compared to the real traffic between 2000 and 2010,

The second step is to assess the traffic forecast established for each supply segment compared to the global one by following the same procedure as described above for the first step.

Each air travel market is taken as a whole for the annual analysis, but also by different time-span and then by market segmentation, by separating the traffic carried out by the different airlines types such as the legacy ones or the charters ones, or the LCCs ones.

The aim is to determine if short-term forecast in crisis time can be improved by including consumer confidence index, before joining back the long-term trend established in “normal times”.

The annual analysis is done for the three case studies through an OLS procedure.

4.3.4 The technique and the software

When estimating the regression coefficients for each independent variable, OLS assumes the following assumptions (Karlaftis, Zografos, Papastavrou and Charnes, 1996):

- The forecast errors are normally distributed with a mean of zero.
- The forecast errors are statistically independent of each other (no autocorrelation).
- The variance of the forecast error is constant across all observations and values of independent variables (homoscedasticity).

The tests used to check these assumptions will be detailed in the section 4.4.

A specific technique of OLS is the stepwise process which in essence, searches out the greatest contributors (between a set of independent variables) to the total variance and effectively rank orders them, in order to select the best regression equation.

Therefore it seems to be a suitable and useful technique to test the explanatory power of the confidence index when added to "pure" economic variables, as this technique will allow to identify if this index could be preferred to other drivers to enter the demand equation. The way the variables are added in a stepwise manner enables to show the effects of additional variables (Taneja, 1976).

Although the model is determined by a stepwise method, additional models may be needed to be built by eliminating any of the independent variables initially listed and introduced in the forecasting software as potential parameters, as the sign of the parameter estimate may be not the expected one. In addition, sometimes a model built with many parameters leads to worse forecasts than a model with fewer parameters. In such cases, it is necessary to simplify the baseline model by eliminating variables.If a choice is needed between several models, the retained model will be determined by both a judgemental process and a formal model evaluation through the checking of various statistical tests detailed in section 4.4.

The software used to build the regressions is the SAS software, and more specifically, the SAS Enterprise Guide 4.2. Enterprise Guide 4 is a point and click interface which uses SAS in-built functions. It is helpful as the user is able to explore the power of SAS without writing the codes, leading to a significant gain in time. In addition, for some specific time series analyses, the software EVIEWS has been preferred.

4.4. Forecasting issues to be considered and associated tests and remedies

Important principles for developing regression models are to use prior knowledge and theory for selecting variables and for specifying the directions of effects and to discard variables if the relationship estimated from the data conflicts with prior evidence on the nature of the relationship. Among the different forecast issues, heteroscedasticity, trends, autocorrelation, omission of causal variables, lagged variables, the real proof of causal relationship and multi-collinearity are the most common ones.

Based on a literature review, Greene (2000), Enders (1993), Wooldridge (1991) and White (1980) of linear regressions and associated issues, the following sub-sections detail the concerns that may be faced when modelling air traffic, the diagnostic tests used and the remedies that may be applied.

It is understood that for any of the OLS that will be run for the three case studies, these assumptions will be systematically checked, but not shown in the main text.

4.4.1. Sample size and number of predictor variables

Multiple regression requires a large number of observations, and they must substantially exceed the number of predictor variables used in the regression. The absolute minimum is to have five times as many participants as predictor variables. There are no generally agreed methods for relating the number of observations versus the number of independent variables in the model. One rule of thumb suggested by Good and Hardin (2009) is shown in equation (7)

$$N = m^n \qquad (7)$$

where N is the sample size, n is the number of independent variables and m is the number of observations needed to reach the desired precision. For example, if a linear regression model had only one independent variable using a dataset that contains N observations and that the analysis needs only m observations to precisely define a straight line, then the maximum number of independent variables his model can support is (*Log* N/*Log* m).

A more acceptable ratio is 10 observations for 1 independent variable, but some researchers argue that this should be as high as 40 for 1 for some statistical selection methods. The rule of thumb based on the text *´´Multivariate Data Analysis´´* by Hair, Anderson, Tatham and Black (1995) for required sample size is stating a minimum of 5 observations for each independent variable included in the analysis, and preferably 15 cases for each independent variable.

In *´´Using Multivariate Statistics´´*, Tabachnick and Fidell (2006) recommend that the required number of observations should be the larger of:

(the number of independent variables x 8 + 50) or

(the number of independent variables + 105).

Following this rule, a linear regression with one independent variable would require a sample of 106 cases. This rule of thumb could be difficult to implement when analyzing air travel markets as reliable and accurate annual data are not easily accessible, while in addition annual aviation statistics are being collected only since approximately 65 years[25].

There is no single method to determine the number of explanatory variables to include in a regression. Among the suggested method, the stepwise regression (cf sub-section 4.3.4) ensures that the model will end up with the smallest possible set of predictor variables to be included in it. The advantage of the stepwise method as being a sequential process for OLS fitting is that it always results in the most parsimonious model, considering the sample size.

For time series analyzed through an ARIMA model, Box and Jenkins, for example, recommended a minimum of 50 observations and it is commonly

[25] The ICAO Statistics Programme has started in 1947.

expected that a model with seasonal effects would need to have several "seasons" worth of data. Once the candidate variables of the model have been determined and the data have been collected and verified, the model is ready to be calibrated using adapted statistical techniques and analysis.

Before running the regression analysis, a series of scatter plots of each independent variable against the dependent variable are examined to identify the linearity of the relationship between dependent and independent variables. Nonlinearity is usually most evident in a plot of the *observed versus predicted values* or a plot of *residuals versus predicted values*, which are a part of standard regression output. The points should be symmetrically distributed around a diagonal line in the former plot or a horizontal line in the latter plot.

The graphical analysis is helpful to identify the relationship between two variables, but also trends, cyclicality and seasonality patterns.

4.4.3. Trends and cyclicality issues

The accuracy of forecasting by historical sequence or trend analysis depends on predictions of changing factors that may keep history from repeating itself. The values for future traffic level are determined by four time-related factors, namely, long-term trends, such as market growth caused by increases in income or decreases in air fares, cyclical variations, such as those caused by the economic cycle, seasonal phenomena, such as weather or holidays and irregular or unique events, such as strikes, wars, and natural disasters. These four factors induce the following types of behavior in the dependent variable: trends, cyclical variations, seasonal changes, and irregular fluctuations. The business cycle, featuring the fluctuation in the level of economic activity, could range from 1 to 10 years and is responsible for cyclical variations in air traffic. It has a significant effect on all segments of the air transport industry, as both business and leisure air travellers are affected by the trough and peaks of the economic cycle. Cyclical variations can be removed by performing a couple of tasks and the most common instruments for this purpose are semi-averages and moving averages. Once the elasticity of the forecast variable with respect to the business cycle index is determined, the observations of the traffic (RPKs) can be adjusted by subtracting the cyclical variation, computed for each point in time. The resulting time series is a trend line free of cyclical variation.

Although the multivariate model is very useful to analyse the influence of many factors on air travel demand, results from estimating regression equations of this type are a matter of controversy in the econometric literature. The results of regressions that appear to have significant diagnostic results, but which, in fact, have no real economic meaning are qualified as spurious regressions (Granger and Newbold, 1974). The spurious regression problem suggests that the dependent and the explanatory variables are moving together through time in a similar fashion, but they do not have any real impact on each other, meaning that the model may be the result of correlation rather than causality.

However, if there exists a relationship to which the variables tend to revert in the long run, the variables are said to be 'co-integrated' and there are a range of time series techniques available that avoid the problem of spurious regression. The concept of co-integration (Granger, 1981) which is the link between non-stationarity and long run equilibrium postulates that a set of variables (all of them being integrated of the same order) exhibit a long-run relationship that is not spurious if the error term resulting from their regression is stationary. If two variables are co-integrated then it is possible to use what is known in the econometrics literature as an error correction mechanism (ECM). In the case of air travel demand and as mentioned by the UK publication on traffic forecasts (2011), there are trends over time, upward trends in traffic, but also in the driving variables such as GDP, as well as downwards trend in air fares. These trends may be non-stationary (they are not following fixed, constant time trends), and using standard regression techniques to establish relationship with non-stationary time series data can result in spurious regressions. In practice, this would mean the significance of the parameter estimates is biased in the upward direction. In that context, the statistical significance of the estimated relationship appears stronger than it really is. Therefore, the standard errors on the estimated parameters are biased, leading to measures of parameter significance and model goodness of fit that are misleadingly high. In order to yield sensible results for a multivariate model, all variables are required to be stationary. Because of the possibility of spurious regression, it is usually advised that variables in time series regressions be detrended or differenced, as necessary, to achieve stationarity before estimation. As an initial step the model variables are tested for their time series properties in order to determine the order and type of non-stationarity with the ADF unit root test. Then and if needed, in order to remove non-stationarity from a time series it could require differencing of successive lags or the removal of trends.

However, it is not always the case that regression models involving non-stationary variables will yield spurious results. Most economic time series have been shown to be non-stationary (Nelson and Plosser, 1982). In spite of this, many economic variables are strongly related to other economic variables in level terms. To study long run relationships between variables it is required that modelling be performed in levels rather than differences. When models are specified in terms of differences, all long term relationships are lost as nothing is assumed to change.

A further consideration is that of sample size. For the three case studies, the sample size is only starting from 1985 and even in 1995 when modelling by supply side segmentation. With such small sample sizes, models transformed into first or higher order differences develop degrees of freedom problems. For meaningful results, model variables should either be stationary or integrated of the same order and when modelled have a co-integrated relationship.

Taking into account these combined factors, it suggests that there is little to be gained by modelling in differences or using the concept of co-integration to produce error correction models. The level of differencing, usually twice or even higher could lead to degrees of freedom problems, taking into account the small sample size for each of the case study. The probability of finding equations with each variable integrated at the same level and possessing a co-integration vector is very low.

Hence, the ECM does not seem a plausible option for the three case studies. Continuing to model in levels and attempting to correct (if needed) for auto-correlated error terms, appears to be the most appropriate method. Such models are able to provide an excellent fit, although they may suffer from several problems which are unlikely to be solved until sample sizes increase significantly.

Nevertheless, there are trade-offs between working with variables that retain their original economic meaning and transformed variables that improve the statistical characteristics of OLS estimation. The trade-off may be difficult to evaluate, since the degree of "spuriousness" in the original regression cannot be measured directly. The methods discussed above will likely improve the forecasting abilities of resulting models, but may do so at the expense of explanatory simplicity.

Therefore, an alternative is to leave the trend and the cyclical variation in the data, meaning that the result is a forecast that reflects the past relationship. Depending on the purpose of the forecast, this might, in fact, be the more realistic approach, in that it reflects the uncertainty induced by the business cycle.

4.4.3. Normal distribution

The distribution of independent variables is important to capturing meaningful relationships in OLS regressions. Non-normally distributed independent variable data can cause analytical difficulties as many statistical tools are based on the assumption of normality of data. Violations of normality compromise the estimation of coefficients and the calculation of confidence intervals. In actuality, it is the residuals that need to be normally distributed, in order for the t-tests to be valid. The estimation of the regression coefficients do not require normally distributed residuals, while if the error distribution is significantly non-normal, confidence intervals may be too wide or too narrow.

To determine normality of variables, a combination of graphical and numerical methods is recommended. The normality assumption implies that the histogram of forecast errors should follow the pattern of a normal distribution centered at zero. If the histogram is observed severely skewed, the violation of the assumption should be investigated.

For sample sizes of residuals relatively small (<50), it is recommended to use the normal probability plots (Q-Q plot) which is a scatter diagram of the forecast errors over the standard residuals. If the forecast errors follow a normal distribution, a straight line should be observed in the probability plot of residuals.

A numerical method for normality test is to compute the Jarque-Bera statistic which is a goodness-of-fit test of whether sample data have the skewness and kurtosis matching a normal distribution.

Another normality test, the Shapiro-Wilk (W)[26] test, is also commonly used. W is the ratio of the best estimator of the variance to the usual corrected sum of squares estimator of the variance. The statistic must be positive and less than or equal to one, and being close to one in order to indicate normality.

4.4.4. Missing data, outliers and influential points

When an explanatory variable is omitted from a regression, the omission can bias the other regression parameters if that variable is correlated with other variables. A similar problem arises when a selected variable is not observed or when it is measured with error. Standard regression models assume that all explanatory variables are known and measured with certainty so that the only source of regression error is the regression model's ability to properly pick up relationships between dependent and independent variables. Measurement errors will tend to decrease co-variances between dependent and independent variables, reducing the values of regression beta coefficients.

Similarly, outliers and extreme observations are likely to cause particularly difficult problems, as ignoring the normality of data and treating them as though it were normally distributed may result in inaccurate results There are a number of possible means for dealing with data non-normality, either by eliminating extreme observations from the sample set (involves a loss of information), or by transforming data points (e.g. original values to logs of original values) to achieve normality of the data series.

Finally , to measure any undue influence on the regression coefficient that may have influential points, DFFITS is the measure of influence available in SAS Enterprise Guide. The DFFITS statistic is a scaled measure of the change in the predicted value for the *i*th observation and is calculated by deleting the *i*th observation. Large values of DFFITS indicate influential observations and a general cutoff to consider is 2.

In the context of the three case studies and taking into account the constraints in terms of data set, the transformation in log values is the privileged way to treat the extreme observation issue. In addition there is a need to let them in the model in order to test specifically the forecasting power of the Consumer Confidence Index in extraordinary times.

4.4.5. Independence of errors and Autocorrelation

There is a need to confirm that there is no autocorrelation which means that the individual value of the dependent variable is not affected by each other. Autocorrelation of the residuals causes the estimate of the residuals variance to be small, implying that an unreliable evaluation may result.

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[26] The W statistic was constructed by considering the regression of ordered sample values on corresponding expected normal order statistics, which for a sample from a normally distributed population is linear. Shapiro and Wilk's (1965) original W statistic is valid for the sample sizes between 3 and 50. The null hypothesis for this test is that the data are normally distributed. The Prob < W value listed in the output is the p-value. If the chosen alpha level is 0.05 and the p-value is less than 0.05, then the null hypothesis that the data are normally distributed is rejected. If the p-value is greater than 0.05, then the null hypothesis has not been rejected.

Violations of independence are very serious in regression models, as serial correlation in the residuals means that there is room for improvement in the model, and extreme serial correlation is often a symptom of a mis-specified model. Serial correlation is also sometimes a by-product of a violation of the linearity assumption and may have the following effects:

- estimated regression coefficients are still unbiased but no longer minimum variance which means they are inefficient
- MSE may underestimate the true variance of errors
- Statistical inference using t-student and F is no longer justified

One widely used method to check the presence of the autocorrelation is the Durbin-Watson (DW) test. The DW statistic is calculated to determine whether the correlation between residuals is statistically equal to zero. The range of DW statistic is always within 0 and 4. Values close to 2 (between 1.4 and 2.6 for a sample size of 50) indicate that autocorrelation does not exist. Values close to 0 and 4 (Gaynor and Kirkpatrick, 1994) indicates positive and negative autocorrelation, respectively. Minor cases of positive serial correlation (DW between 1.2 and 1.6) indicate that there is some room for fine-tuning in the model, by considering adding lags of the dependent variable and/or lags of some of the independent variables. If there is significant negative correlation in the residuals (DW greater than 2.6), there is a possibility that some variables have been over differenced. Differencing tends to drive autocorrelations in the negative direction, and too much differencing may lead to patterns of negative correlation that lagged variables cannot correct for.

The violation of this assumption can also be examined by plotting residuals versus time (called time plot of residuals).This autocorrelation plot of residuals should not display any visible trend if autocorrelation is not present. Ideally, most of the residual autocorrelations should fall within the 95% confidence bands around zero, which are located at roughly plus or minus 2 over the square root of the number of observations.

More generally speaking, serial correlation usually indicates a fundamental structural problem in the model, leading to reconsider the transformations (if any) that have been applied to the dependent and independent variables.

4.4.6. Homoscedasticity

The last assumption supporting both OLS and BJ estimates is the constant variance of residuals which is called homoscedasticity. Residuals with non-constant variance are said to be heteroscedastic (unequal scatter), thus distorting the measure of unexplained variation and producing misleading statistical tests. Despite the fact that the OLS regression might still be unbiased, it will not produce the minimum variance estimators. Indeed, violations of homoscedasticity make it difficult to gauge the true standard deviation of the forecast errors, usually resulting in confidence intervals that are too wide or too narrow. In particular, if the variance of the errors is increasing over time, confidence intervals for out-of-sample predictions will tend to be unrealistically narrow. Heteroscedasticity may also have the effect of giving too much weight to small subset of the data when estimating coefficients.

Heteroscedastity can be tested by plotting residuals either over time or against the estimated values of the dependent variable, and if the variances show no visible pattern, the homoscedasticity assumption is verified.
In that case, the model is correctly specified as they are homoscedastic and non-correlated. If the residuals are not white noise, the analysis of their correlogram gives indications of how to modify the model initially defined, and this procedure is an iterative process. The White test is another statistical test that establishes whether the residual variance of a variable in a regression model is constant meaning that it meets the homoscedasticity assumption.

There are a number of potential causes of heteroscedasticity. Among them are increases in the absolute values of residuals due to trending in either the dependent or independent variables, differences in sub-populations, clustering of sub-groups and model misspecifications.

In the specific context of air travel demand, the air travel rate of penetration is highly correlated to the income and besides, within a population the traveler has an average revenue higher than the average. Then air transport consumption should evolve as a function of not only the mean purchasing power but also of the income distribution. This leads to consider that heteroscedasticity is occurring when evaluating air travel demand.

Families with low annual incomes will spend relatively little in air travel and the variations in expenditures across such families will be small.

On the opposite, for families with large incomes, the amount of discretionary income will be higher, and the mean amount spent in air travel will be higher. However, there will be also greater variability of air travel consumption among such families, because high family income is a necessary but not sufficient condition to get a high value on expenditures in air travel, and this is resulting in heteroscedasticity.

Therefore, the traditional econometric modeling of air travel demand is probably over stating income elasticity. Although it is assumed that air travel grows linearly with GDP growth and fares decrease, it is still remaining one part of travel growth that is not explained.

4.4.7. Misspecification

Misspecification of the functional form of the regression is a potentially more serious problem than heteroscedasticity in that it can lead to biased and inconsistent estimates of parameters. In fact, heteroscedasticity can often simply be a by-product of regression misspecification.

There are several ways to detect mis-specified functional form of the regression. One very simple test of variable misspecification involves the Ramsey Regression Equation Specification Error Test (RESET)[27] which is a general specification test for the linear regression model. The OLS assumes that errors in prediction of each value of the dependent variable have an

[27] More specifically, it tests whether non-linear combinations of the fitted values help explain the response variable. The intuition behind the test is that if non-linear combinations of the explanatory variables have any power in explaining the response variable, the model is mis-specified

expected value of zero. If error terms are randomly distributed with zero expected values, then no non-linear functions of independent variables should be added to the regression model.

After having checked the preliminary assumptions for OLS, as described in the previous sub-sections, the next step is to obtain a correlation matrix between explanatory variables in order to prevent multi-collinearity issues.

4.4.8. Multi-collinearity issues

Multi-collinearity occurs when two or more explanatory variables are highly correlated with each other which leads to unreliable estimates of model. The presence of multi-collinearity creates lower t-statistic values because the standard errors of the regression coefficients are largely overestimated. Without a multi-collinearity evaluation, it is no longer possible to determine which of the independent variables are relevant in the regression equation. Using the capabilities of SAS the Pearson's correlation coefficient is computed between all the independent variables. This coefficient measures how variables are linearly related. It ranges in value from -1 (a perfect negative relationship) and +1 (a perfect positive relationship). A value of 0 indicates no linear relationship.

Although no universally acceptable criteria of determination of multi-collinearity has been established, correlations of 0.70 and above as well as a low t-statistic value are frequently mentioned as benchmarks.

Independent variables are almost always correlated to some degree, so the influence of multi-collinearity on the regression results is a matter of degree (Taneja, 1976). However, it is noteworthy that multi-collinearity does not violate any of the assumptions of OLS regression, and thus the parameter estimator under such circumstances is still B.L.U.E. (Best Linear Unbiased Estimator). The problem of which level of correlation constitutes multi-collinearity is still under debate in the statistical world and the positions vary from conservative to liberal:

a) <u>Conservative</u>: If two variables have a correlation coefficient greater than R=0.5, one of them must be eliminated from the equation.
b) <u>Jensen:</u> If two variables have a correlation coefficient equal to or greater than R=0.9, one of them must be eliminated from the equation.
c) <u>Liberal</u>: If the equation user can live with the assumption that the relationship between/among the variables will continue unchanged, then multi-collinearity is not a problem.

A general rule is that the Variance Inflation Factor (VIF) should not exceed 10 (Belsley, Kuh, & Welsch, 1980).

Multi-collinearity can usually be identified by checking the logical correlation coefficients between the dependent and independent variables. Significant but 'wrong' sign of regression coefficient between the dependent and independent variables shows severe multi-collinearity. A second step is to estimate the correlation matrix for independent variables to identify high correlation coefficient (the issue will be to determine the threshold of the coefficient level indicating multi-collinearity) which indicates multi-collinearity problem. Finally, values of the Variance Inflation Factor (VIF) exceeding 10 can indicate multi-collinearity. For the three case studies analyses, a combination of these three tests is used to assess multi-collinearity.

It is worth mentioning that the effect of multi-collinearity can be reduced by increasing the sample size (not always possible due to data access limitation) and eliminating redundant independent variables. Multi-collinearity can be problematic if the forecasting purpose is to allocate unbiased explanatory power to each variable in a context of a small number of observations. However, according to Farrar and Glauber (1967) multi-collinearity, is not a problem in forecasting with OLS, provided that the same pattern which existed between two variables in the past, persists in the forecast period.

Once the model is calibrated, some statistical tests are performed to check the assumptions made during the regression analysis. The significance of the regression coefficients are examined statistically and the forecasting accuracy of the model is evaluated

4.4.9. Statistical tests of the regression coefficients

Once the regression model has been tested for the underlying assumptions of OLS, each regression coefficient is analyzed to check whether the estimated sign of the coefficient is consistent with the expectations of the sign. According to the economic theory, the coefficient for GDP or income in air travel demand model should be positively related, while the coefficient for yields should be negatively related. Then, a graph of the observed data vs. the modelled ones is generated to determine the goodness of the fit which shows how well the model works.

The next step is to perform statistical tests to examine the forecasting accuracy of model and the statistical validity of the regression coefficients. The magnitude of the coefficient are also evaluated in order to make sure that it is reasonable within the context of the computations.

A Student´s *T-test (t)* is used to examine whether each independent variable contributes significantly (i.e. statistically different from zero) to the model. A *t*-value greater than 2 is considered to provide a statistically meaningful relationships between the dependent variable and the corresponding independent variable.

Any explanatory variable with a wrong sign, wrong magnitude or statistically insignificant must be dropped from the regression equation.

Multicollinearity and violation of constant variance assumption may cause the wrong sign of the regression coefficient. In addition, when omitting an insignificant explanatory variable from the equation provides a better prediction of the model. All these issues should be considered when selecting the final regression equation.

4.4.10. Overall significance of the model

A standard measure of goodness-of-fit used to evaluate regression model is the *F* statistic along with the coefficient of determination R-Squared (*R2*) or Adjusted R-Squared (*Adj R*2).

The *F*-statistic is used to test whether there is a statistically significant relationship between the dependent and the independent variables. It is the ratio of the mean square regression to the mean square error and it evaluates the null hypothesis that all regression coefficients are equal to zero versus the alternative that at least one does not. Thus, the F-test determines whether the proposed relationship between the response variable and the set of predictors is statistically reliable, and can be useful when the research objective is either prediction or explanation.

The *F* statistic is used to tell how well the model fits the observed data. A significant F-test indicates that the observed R-squared is reliable, and is not a spurious result of oddities in the data set. Whereas the *F* statistic is a useful test of the estimated model’s ability to explain any variation in the dependent variable, it does not provide confirmation about the strength of the explanatory power.

The value of *R*2 measures the percentage of the variation in the dependent variable that is explained jointly by the independent variables . Although a high *R2* does not necessarily mean an “appropriate” model, an “appropriate” model is expected to have a reasonably “high” *R2* . The better the fit of the regression model, the closer *R*2 is to 1. The *R2* statistic is calculated by comparing the explained variation of the model to the total variation. The value of *R2* always increases as the number of independent variables is increased in a regression equation, meaning that the goodness-of-fit of the model appears to improve by just adding additional independent variables.

However, Adjusted R-squared incorporates the model’s degrees of freedom, and it will decrease as predictors are added if the increase in model fit does not make up for the loss of degrees of freedom. Likewise, it will increase as predictors are added if the increase in model fit is worthwhile.

Therefore Adjusted R-squared is always recommended when comparing two alternative models containing an unequal number of independent variables or two alternative models using different functional forms but the same sets of independent variables, as by using Adjusted R-squared, the benefits obtained by adding additional independent variables are balanced against the cost of losing additional degrees of freedom. The Adjusted R-squared is used for the three case studies to measure the goodness-of-fit of the models.

In some cases, a high R-squared is not necessary or relevant, notably when the interest is in the relationship between variables, and not in prediction which is the aim of the three case studies analyzed.

However, in some cases, it is necessary to involve one or more additional tuning parameters in order to select a “best” model from a class of models.

Mallows C(p) Selection Criterion, is used to assess the fit of a regression model that has been estimated using OLS. It is applied in the context of model selection, where a number of predictor variables are available for predicting some outcome, and the goal is to find the best model involving a subset of these predictors. The Mallows C(p) [28] is one of the retained test for the three case studies.

Another test, the Akaike Information Criterion (AIC) is measuring the relative goodness of fit of a statistical model by providing a relative measure of the information lost when a given model is used to describe reality. AIC values provide a means for model selection, but if all the candidate models fit poorly, AIC will not give any warning of that. To apply AIC in practice, there is a need to compare AIC values for 2 models, in order to determine the model that minimizes the information loss. Taking into consideration this criterion alone cannot allow to choose with certainty, but it minimizes the estimated information loss.

With respect to Bayesian Information Criterion (BIC) or the Schwarz criterion (also SBC, SBIC), it is also a criterion for model selection among a finite set of models, based, in part, on the likelihood function, while closely related to AIC. When fitting models, it is possible to increase the likelihood by adding parameters, but doing so may result in over fitting. The BIC resolves this problem by introducing a penalty term for the number of parameters in the model. The penalty term is larger in BIC than in AIC which means that unexplained variation in the dependent variable and the number of explanatory variables increase the value of BIC. Hence, lower BIC implies either fewer explanatory variables, better fit, or both. Given any two estimated models, the model with the lower value of BIC is the one to be preferred.

4.4.11. Evaluation of model forecasts over different time-spans

In order to determine the model accuracy or the tight fit of a model to data, there are several forms of forecast error calculation methods used, among them the percentage error, the sum of squared errors of prediction (SSE) and the Root Mean Squared Error (RMSE).

The percentage error is the discrepancy between an exact value and the forecast value to it. By convention, the error is defined using the value of the outcome *minus* the value of the forecast. The relative error is derived from the absolute error which is the magnitude of the difference between the exact value and the estimated one, and the relative error is the absolute error divided by the magnitude of the exact value. The percent error is the relative error expressed in terms of percentage.

The residual sum of squares (RSS) is the sum of squares of residuals. It is also known as the sum of squared residuals (SSR) or the sum of squared errors of prediction (SSE). It is a measure of the discrepancy between the data and an estimation model. A small RSS indicates a tight fit of the model to the data.

The RMSE is a measure of standard deviation of the forecasting error and is defined as the difference between the observed data and the forecasted value generated by the model. The RMSE is the square root of the variance of the

[28] C(p): S is the MSE for the full model, and it is the error sum of squares for a model with p parameters including the intercept and n denotes the number of observations. For each model size P we can plot the ´´S´´ against ´´P´´. Mallows recommends choosing the model whose S is closest to P upon the first approach of P, i.e. the first time a model's S is "close" to P.

residuals. It indicates the absolute fit of the model to the data, which means how close the observed data points are to the model's predicted values. Whereas R-squared is a relative measure of fit, RMSE is an absolute measure of fit. As the square root of a variance, RMSE can be interpreted as the standard deviation of the unexplained variance, and has the useful property of being in the same units as the response variable. Lower values of RMSE indicate better fit. RMSE is a good measure of how accurately the model predicts the response, and is the most important criterion for fit, if the main purpose of the model is prediction.
Two types of RMSEs are usually applied to determine the forecasting accuracy of a model: "within-sample" RMSE is calculated for the models that use the entire available historical data, while "out-of-sample" RMSE can be estimated for the models whose calibration are conducted by portioning the whole observed historical data into several subsets. The first subset is used to calibrate the model and generate the forecast. The forecast is then used to compare not only with the actual data from the first subsets, but also with the observed data from the second subset that is not employed in the model calibration. RMSE can be used to select the best forecasting model by simply choosing the model with the smallest RMSE. However, it is noteworthy that comparisons of RMSE for alternative forecasting models using different transformations of the data is not relevant. Due to the process (cf section 4.3) retained for the three case studies, the models will be evaluated with both "within-sample" and "out-of-sample" RMSE calculations, and the assessment of accuracy is made through the evaluation of the forecast error.

Some additional tests may need to be computed for checking purposes, notably on exogeneity of the regressors as well as on the structural stability of a model.

Some regressors may be endogenous which means that one or more regressors are correlated with the error term. In this situation, OLS cannot consistently estimate the causal effect of the regressor on the dependent variable. It is a required standard assumption in regression analysis because if the supposed independent variables are not independent of the error term, then the estimated regression coefficients are not consistent in the OLS estimating equation. In addition, the regressors are more efficient under exogeneity. There are 4 main reasons why the regressor and the error term might be correlated

a) Simultaneous equations bias which implies that a regressor is correlated with the error term
b) Omitted variable bias
c) Lagged dependent variable which implies that the model includes a lagged dependent variable and has a serially correlated disturbance
d) Errors in variables

In order to run the exogeneity test, a t-test is ran in equation (9) on the mean of the errors, in order to test the hypothesis H0 and H1, rejecting or not the exogeneity assumption as shown in equation (8).

$$HO: E(\varepsilon) = 0 \qquad H1: not\ \ H0 \tag{8}$$

$$t = \frac{E(\varepsilon)-0}{se(\varepsilon)} \sim t(n-2) \tag{9}$$

It may be of interest to test for stability of regression coefficients between two periods. A series of data can often contain a structural break, due to a change in policy or sudden shock as for instance it was the case for air travel demand after 9/11. A change in parameters between two periods is an indication of structural change. The Chow test statistic is testing the structural stability of a model during a given period by checking whether a single regression line or two separate regression lines fit the data best.

The model in effect uses an F-test to determine whether a single regression is more efficient than two separate regressions involving splitting the data into two sub-samples. After running the 3 regressions (with the same number of parameters) using first all the data and then before and after the structural break, it is necessary to collect the 3 RSS: RSS_1, RSS_2 and RSS_3 in order to compute the test, as indicated in equation (10).

$$Chow = \frac{(RSS1 - RSS2 - RSS3)/_{k}}{(RSS2 + RSS3)/_{(n-k)}} \sim F_{k,n-k} \tag{10}$$

The F value is compared with the critical values in the F-test tables, according to the degrees of freedom, in order to be able to conclude, the null hypothesis being that there is no structural break.

Adopting a practical approach, the first case study attempts to apply the described methodology and processes, in order to provide a formal evaluation of consumer confidence indices as eventual explanatory variables to determine air travel demand. The performance appraisal of this index is first tested for the Domestic US air travel market, as it was the first liberalized market and it is still the most important world air travel market, representing 22% of the global world RPKs.

5. FIRST CASE STUDY: THE US DOMESTIC AIR TRAVEL MARKET

Major trends in the traffic growth must be analysed to highlight key dynamics that govern the domestic air travel demand. The air travel industry evolved through periods of industry deregulation, economic growth bubble, the aftermath of the attacks of 2001 and the financial and economic crises of 2008 and 2009.

5.1. Different phases of traffic growth

The analysis of the traffic pattern between the successive 10-year periods, since 1970, has shown different growth rates, as shown in Figure 12.

Deregulation has brought enormous changes to the US airline industry, and during the following cycle of economic growth, the dynamics of supply and demand fundamentally shifted, as major carriers focused on high-revenue operations targeted toward business travellers.

In parallel, a new generation of “no-frills” carriers has emerged to exploit the niche market left available, and leisure travelers began to use the services of newer low-fare airlines, the so-called Low-Cost Carriers (LCCs). As a consequence the US Domestic traffic has more than doubled between 1978 and 1997 and the overall airfares dropped by 40% in real terms during this twenty-year period.

On the other hand, the oil crises, the Iran-Iraq war, the two Gulf wars, the WTC attack, SARS (Severe Acute Respiratory Syndrome), and more recently the financial crisis and the economic recession are among the forces that have constrained the growth of the US air travel demand.

Although the virus SARS was centred in Asia where China, Hong Kong, Taiwan and Singapore were the worst affected countries (Canada was also affected to a lesser extent), the World Health Organization (WHO) considered it as a global health emergency.

According to a study produced by RITA[29], SARS was listed among the significant events that have impacted U.S. domestic passenger aviation operations.

However there could have been some intertwined effects as during the same period in which the SARS virus was spreading, the US led invasion in Iraq officially lasted from 20 March to 1 May 2003. The war in Iraq created uncertainty for travelers around the globe, in particular for those with plans to travel to long haul destinations.

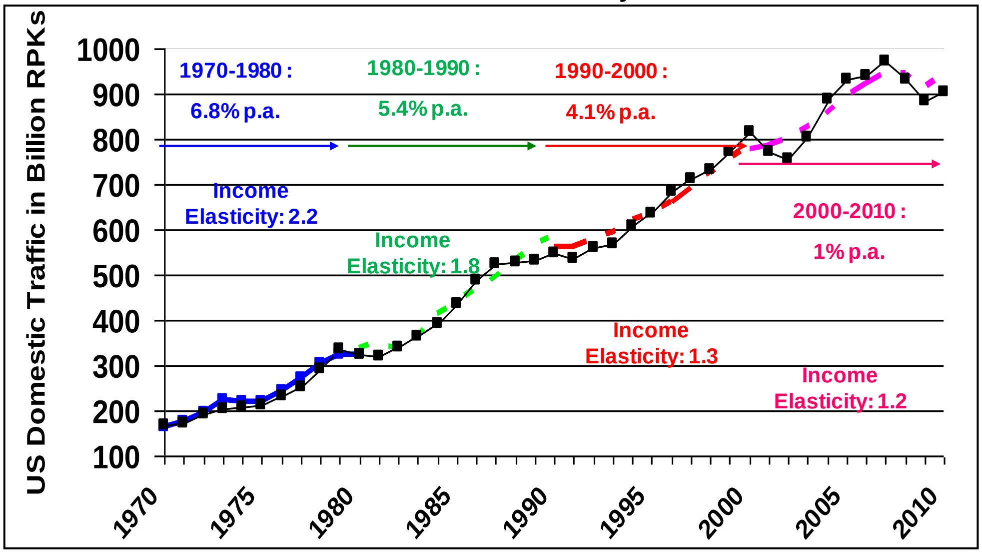
The SARS epidemic and the war in Iraq came at a time of high oil prices and overall weak economic growth in major industrialised economies. This also may have added additional impacts on peoples’ travel behaviour in the Domestic US market.

Besides, the segmentation of airline supply, and intra-industry competition are among the most critical forces that are driving the current reshaping of the US airline industry.

[29] http://www.bts.gov/publications/special_reports_and_issue_briefs/special_report/2012_03_33/html/entire.html

The declining income elasticity of traffic, measured through a regression equation of the US Domestic traffic and the Real GDP is showing changes in passenger dynamics and behaviour, suggesting that there is no more a clear distinction between the business and the leisure segments.

Figure 12:.US Domestic traffic between 1970 and 2010 and evolution of the income elasticity



Source: US DoT

The traditional relationship between traffic and GDP needs to be revisited and refined. As a matter of fact it could justify the introduction of new parameters in the forecasting equation, like the confidence concept

5.2. Air travel demand levers in the US

Taking into account the existing demand for the domestic US air travel market, business travelers represent about 51 %, tourists 12% and Visiting Friends and Relatives (VFR) passengers account for 35%.

In 2010, within the US population, the propensity to fly is estimated at 3 trips per head of population higher than the world average.

According to Pavaux (1984), in the eighties, the propensity to fly in the US was of 2.2 trips per person, which was (related to the population size) more than twice that of the EU estimated at 0.9 trips per person.

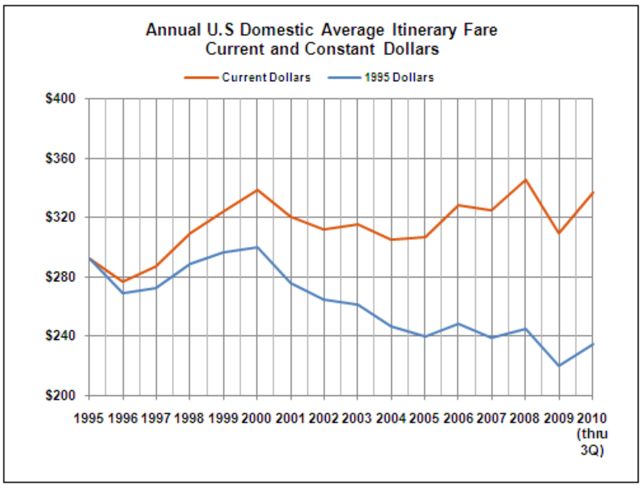
In an analysis reported by a Boeing senior executive, 10% of the US population with income less than US$10 000 traveled by air, while 45% with income comprised between US$ 50 000 and US$ 75 000 traveled, and 75% of people with income higher than US$ 100 000 traveled (Austin, 2000).

It confirms that, air transport consumption is evolving as a function of not only the mean purchasing power but also of the income distribution, and in parallel, it is generally admitted that there is a correlation between the income level and the number of business travel.

In the leisure segment the amount of money that people plan to spend on air travel is linked not only to the air fare but also to the leisure package which includes the airline ticket price and the hotel and ground costs.

According to the US Bureau of Transportation Statistics (BTS)[30], at the end of 2010, the average daily room rate was around US$ 100 and the average domestic airfare ticket at US$ 340, approximately at the same level in current dollars than in 2000. However in real dollars the decrease was substantial as shown in Figure 13, here below. This means that in the last ten years, the willingness to take air travel has been mainly linked to the existing airfare offer.

Figure 13: Annual U.S Domestic Average Itinerary Fare



Source: US Bureau of Transportation Statistics

On its internet site Research and Innovative Technology Administration (RITA)[31] is giving the following precisions for this graph:

´´Fares are based on domestic itinerary fares, round-trip or one-way for which no return is purchased. Fares are based on the total ticket value which consists of the price charged by the airlines plus any additional taxes and fees levied by an outside entity at the time of purchase. Fares include only the price paid at the time of the ticket purchase and do not include other fees paid at the airport or on-board the aircraft. Averages do not include frequent-flyer or "zero fares" or a few abnormally high reported fares. The constant values are calculated using Bureau of Labour and Statistics (BLS)[32] Consumer Price Index´´.

Since 2001, the changes that have occurred in air transport, notably due to increasingly hassling security procedures, have made air travel less convenient, and some substitutes have been found for both the business and the leisure travellers.

Among the different drivers, one is of particular importance to the leisure segment of the air travel demand and is related to the equilibrium between the amount of money that people have to spend for travelling, the existing fares offers, their disposable income and their confidence in the future. Hence propensity to fly seems to become more directly linked with consumer confidence and to the ticket price.

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[30] http://www.bts.gov/programs/economics_and_finance/air_travel_price_index/html/ (date accessed July 2011)
[31] http://www.bts.gov/xml/atpi/src/index.xml (date accessed July 2011)
[32] http://www.bls.gov/cpi/

With an understanding of how Americans spend in place, then it is easier to examine how air travel consumption ties into the picture for the Consumer Confidence Index of the U.S. citizens and their disposable incomes.

5.3. Impact of the US economic picture on air travel spending

Consumer spending is the constant that drives US economy and Americans have experienced a massive increase in disposable income over the past forty years. The more than doubling of real disposable income means increased consumer purchasing power and personal consumption expenditures. The annual data shows not surprisingly a trend of consistent growth every year, for both disposable income which represents the purchasing power and consumption.

In 1990, 90% of total real personal disposable income was spent on real personal consumption in the same year. This 90% propensity to consume remained roughly steady during the nineties, before escalating and reaching a peak in 2005 at 95%, while in 2010 it is back to the percentage level registered in 1995.

Based on figures released by the US Bureau of Labour and statistics (BLS)[33], a comparison analysis of the three categories of consumption expenditures, namely durable goods (e.g. cars, home appliances), non-durable goods (e.g. food, clothing) and services (work done for consumers, as dry cleaning or air travel) have remained steady since 1995 (Thomas, 1996) at about 12%, 22% and 66% respectively for each category.

Between 1995 and 2000, the U.S. economy has benefited considerably from the "wealth effect" created by the large increase in market equity values. This has resulted in unprecedented increases in both consumer spending and consumer confidence which has reached in 2000 its highest level in more than three decades. An increase of that magnitude in the propensity to consume shows Americans had neither fears of job security nor worries of savings. This escalation finally began to reverse with the beginning of the 2001 recession.

In the United States, the aftermath of 2001 has changed the drivers of demand for air travel, and consequently the stable pattern of spending on air travel established since the mid eighties.

More recently, in 2008 and 2009 the world economy faced a severe and synchronized recession, leading to significant changes which heavily impacted the air transport industry. This difficult situation began in the first half of 2008, prompted by high fuel prices which peaked at about $150/barrel[34] in July 2008, and was exacerbated in the second half of 2008 by the credit crunch and the near collapse of the global financial system, plunging the world into a downward spiral of recession which registered the first negative growth of the global economy since the Great Depression of 1929. Mounting job losses and falling asset values have held back consumer spending in discretionary areas like air travel, while deteriorating markets and tightening credit have forced operators to slash capacity, investments and payroll.

[33] http://www.bls.gov/ (date accessed July 2010)
[34] http://www.eia.gov/ (date accessed July 2011)

The roots of the 2009 economic crisis may be traced to the collapse of the 2001 internet bubble, when U.S. interest rates were slashed to make borrowing easier in order to spur home buying. The lower-than-low rates were also used to further expand mortgage-based credit to the so-called No Income No Job and Assets (NINJA) borrower market. A positive reinforcement loop was therefore established between increasing debt and housing prices, leading to the eventual collapse of the housing bubble in 2008. Interest rates continued to be cut even further and the credit expansion flowed into commodity speculation and foreign currency.

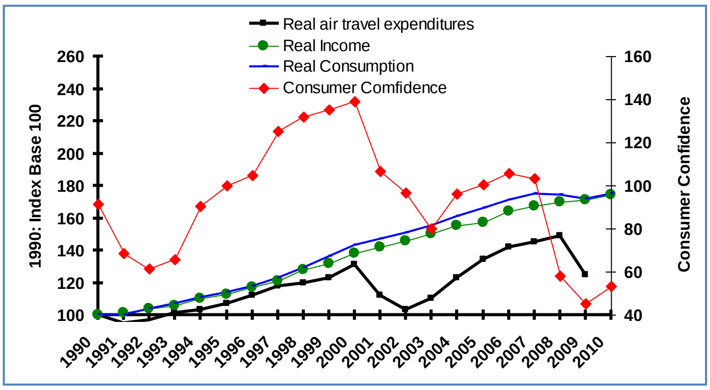
Oil, food and gold prices jumped to historic highs and the U.S. dollar depreciated to historic lows. As a result of the plummeting stock market, the capital value of airlines halved in 2009 compared with early 2008, while limited access to capital markets further complicated cash flow availability.

However, the United States has enacted large fiscal stimulus packages to offset the reductions in private sector demand caused by the crisis, with two packages totalling nearly US$1 trillion during 2008 and 2009, in order to support national consumption levels. Despite these massive injections, 2008 and 2009 crises hit the US air transport, tourism and services sectors harder than other areas of the economy.

They have heavily impacted the US air transport growth and profitability, as the leisure traveller had less or no cash to spend on holidays, and business clientele continued to employ technology-based alternatives to travelling by air. In the first half of 2008, air travel demand was affected by higher fuel prices leading to increased airfares and a decline in consumer discretionary spending on leisure travel. This sharp declining trend in air transport demand and air transport spending by passengers was amplified by the fallout from the global financial crisis in the second half 2008, culminating in the 2009 recession, despite 12 consecutive months of ticket price reductions intended specifically.

Figure 14 shows how air travel expenditures (expressed in real terms) in the US, has dropped from its historical level of around 1.5% to 0.7% of the U.S. real personal consumption.

Figure 14:.Air travel spending, Income, Consumption and confidence



Source: IHS/Global Insight, BLS and DoT

The same pattern was observed for the ratio of air travel spending on real income while the propensity to consume has been stable at 97%, and consumption growth has outpaced income growth. This means that on a proportional basis Americans today are spending considerably less on flying than in previous years.

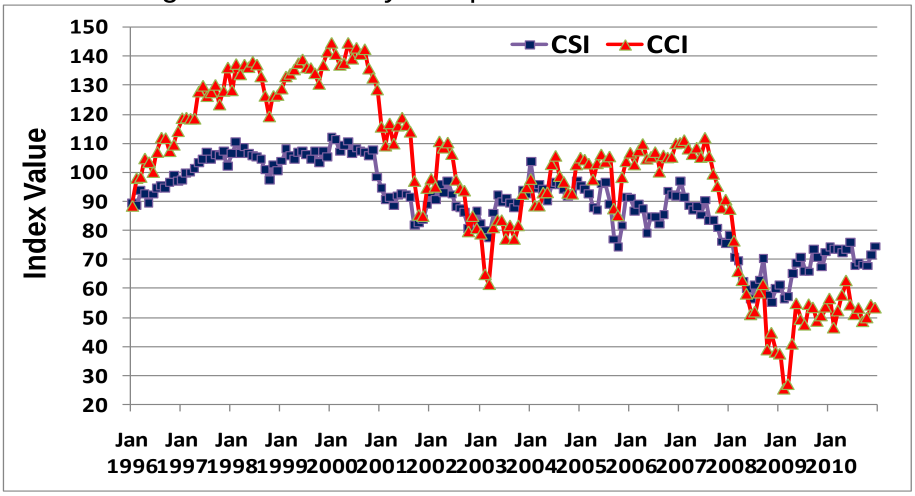
During the economic slowdown, consumption has been resilient mainly on durable goods, thanks to low interest rates, while air travel expenditures seem to have followed the path of a low consumer confidence index, most probably linked to liquidity constraints.

5.4. The two US consumer confidence indices

The survey results considered in this case study are the two measures of consumer confidence in the U.S.A: the Consumer Sentiment Index (CSI), published by the University of Michigan and the Consumer Confidence Index (CCI), issued by the Conference Board. Both surveys base their overall index of consumer confidence on five questions reflecting consumer attitudes and expectations. Although the two surveys measure the same concept, they are based on different sets of questions. Therefore, it is important to understand the key differences in the questions as well as in the sample size, the survey methodology, and the index formulation.

The most important methodological differences between the two surveys concern sample size, which affects sampling error, and index construction, which affects the index range of movement. The survey timing and release schedules also differ which is a relevant consideration when conducting real-time analysis.

Figure 15:.Monthly comparison of CCI and CSI values



Source: IHS/Global Insight

University of Michigan conducts its survey by phone throughout the month. Its sample size is 500, and final figures are made available at the end of the month. The Conference Board sends out a mail survey at the end of the prior month to a sample size of 3,500. Revised data based on the full monthly sample are released the next month's preliminary figures and are not subject to further revision.

Both the University of Michigan (Appendix B) and the Conference Board (Appendix C) base their overall index of consumer confidence on five questions that are part of a broader survey of consumer attitudes and expectations. Although the two indexes broadly measure the same concept which is public confidence in the economy, they are based on different methodologies leading to the result that CCI has a wider range of movement than CSI and sometimes give conflicting signals.

Following September 11, 2001, the two indices fell an average of 21% through March 2003, reaching their lowest levels in nearly a decade. During the same period, US real personal consumption expenditures grew by only 4.9%, compared with a 6.6% rate of growth over the two previous years when consumer sentiment was higher.

In order to interpret movements in these two series, it is important to understand some key differences in the specific questions that are asked as well as in sample size, survey methodology, and index formulation.

Each set of questions asks respondents to assess present and future economic conditions, and in addition to the overall index, both organizations report two component indexes, the Present Conditions Component (or Current Conditions for University of Michigan) and the Expectations Component

5.4.1. Current versus expected components of the consumer confidence

In each survey, two of the five questions ask respondents to assess present economic conditions.

The **Present Conditions** questions receive a 40 percent weight in each overall index. The Conference Board's present conditions component takes a "snapshot" approach, asking respondents to evaluate current business conditions and job availability. Because of the nature of the questions, the Conference Board's present conditions component closely tracks the nation's unemployment rate. Michigan asks respondents to comment on the advisability of big-ticket household purchases and to assess changes in their own financial situation. Michigan's present conditions component is less closely tied to labor market conditions and its level tends to reflect recent changes in the economy rather than the level of economic activity. These differences are reflected in the cyclical behavior of the two present conditions component indexes.

Regarding the ***Expectations Component**, t*he three questions that ask about consumers' expectations are fairly comparable in the two surveys. The Conference Board survey asks about expected changes in business conditions, job availability, and respondents' income over the next six months. Michigan's poses questions on expected business conditions, both over the next year and over the next five years, and expected changes in the respondent's financial situation over the next year. The expectations components in the two surveys are highly correlated with each other.

As shown in Figure 17, the CSI Current value is always above the CSI Expected one, showing that when people are confident about their present condition, the future is always darker in their mind than their current status.

5.4.2. The link between consumer confidence and economic variables

In parallel, when modelling the CSI between January 1996 and January 2011 (N=181), the best estimation, according to the economic variables available for this study, was found with the RU as explanatory variable with an expected inverse correlation sign, while the GDP (in value and in growth rate) has not appeared as significant enough to enter the equation. Following the inclusion in the stepwise regression of the real oil price (WTI for the US market), the RMSE decreased significantly, the adjusted R^2 was improved from 0.5 to 0.70 and the goodness of the fit was greatly improved, as shown in Table1 and Figure 16.

Table 1: Modeling CSI with economic regressors

Number of Observations Read	181
Number of Observations Used	181

CSI Model parameter estimates with RU as explanatory variable

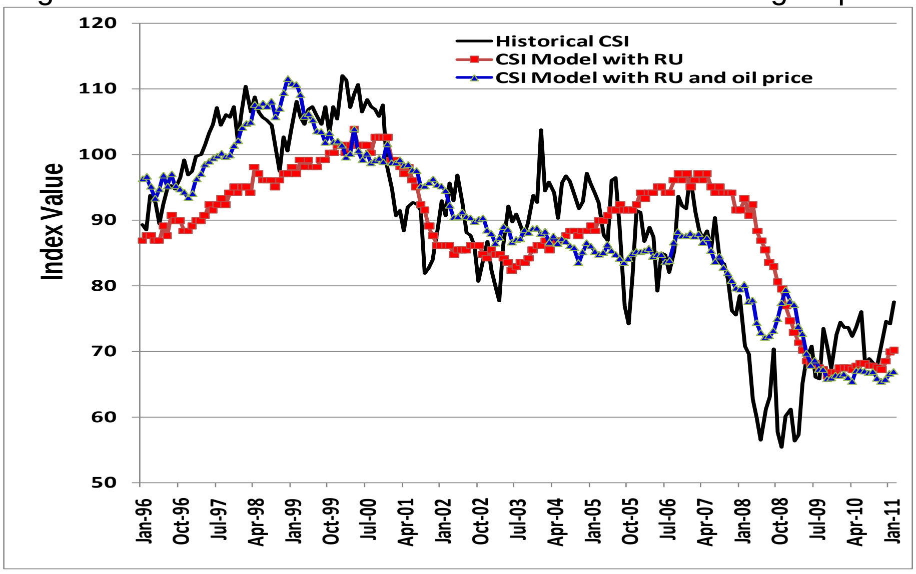
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	5.2561	0.05875	89.47	<.0001
LnRU	1	-0.45965	0.03428	-13.41	<.0001
Root MSE	**0.119**	R-Square	0.4997		
Dependent Mean	4.477	**Adj R-Sq**	**0.497**		
Coeff Var	2.652				

CSI Model parameter estimates with RU and WTI as explanatory variables

Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	5.51918	0.05064	108.98	<.0001
LnRU	1	-0.30999	0.0294	-10.54	<.0001
Ln WTI	1	-0.14243	0.01259	-11.31	<.0001
Root MSE	**0.091**	R-Square	0.7082		
Dependent Mean	4.477	**Adj R-Sq**	**0.705**		
Coeff Var	2.031				

The consumer confidence index exhibits high or low moves that cannot be explained by movements in economic indicators such as GDP growth. This strong correlation of the confidence index with the oil price and therefore with the jet fuel price is confirming its potentiality as a driver for air travel demand forecast.

Figure 16:.Goodness of the fit for CSI models including oil price

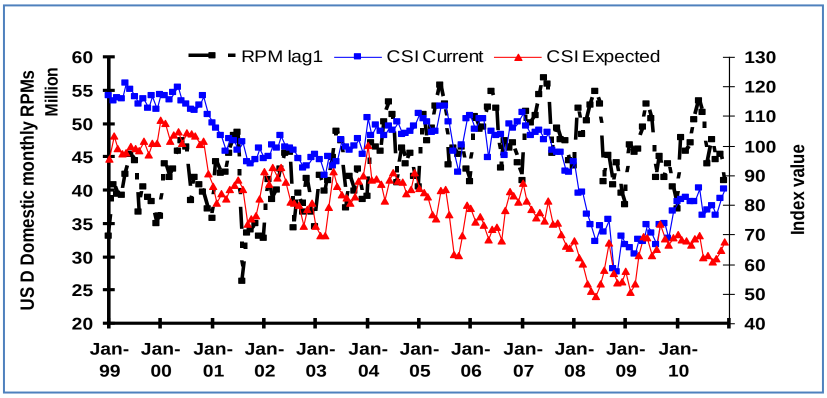


The main issue with the consumer confidence index stays in the availability of forecasts for the index value, as even when they can be found, they are forecasted on annual averages showing only trends.

5.4.3. The link between confidence and Domestic US air travel demand

When comparing the indexes moves with the monthly traffic evolution, both the CSI current and expected values seem to be correlated with the traffic value lagged at the rank 1, as shown in Figure 17.

Figure 17:.Evolution of US Domestic monthly RPM and confidence indices



Source: BTS, IHS/Global Insight

For monthly data, the domestic traffic, expressed in Revenue Passenger Miles (RPMs) is taken from the Bureau of Transportation Statistics (BTS) which publishes monthly passenger traffic data reflecting 100% of scheduled operations for U.S. airlines reporting "T-100 Market" data.

The objective is to check if RPM and consumer confidence have stable long-run relationships, in order to determine at a further stage if short-term forecast, in crisis time can be improved by including consumer confidence as explanatory variable , before joining back the long-term trend established in “normal times”.

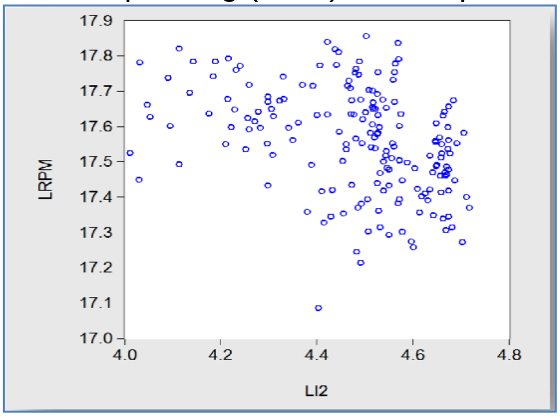
Before applying a BJ model to the US Domestic monthly traffic data, it is obvious that this time series has seasonality properties associated with a trend component and the non-seasonal BJ procedure cannot be ran (cf Section 4.4) with that kind of sample.

After having checked for each consumer confidence series, namely CCI, CSI, CSI Current and CSI Expected, the series retained as the most significant to be studied are Log RPM and Log CSI Current and they are starting from January 1996 to December 2010 which represents a sample of 180 observations. The monthly RPM data series were transformed into a non-seasonal one, while it is noteworthy that the consumer confidence index series are already seasonally adjusted.

Then, an ADF Unit Root test with intercept and trend was carried out in order to check the stationary or not of the 2 series of data. The unit root test is used to identify if air travel and consumer confidence have stable long-run relationships with one another as opposed to spurious regression. The intent is

to determine if they are co-integrated, and the first requirement to use this procedure is to check if these variables are stationary.
The stationary series found for Log RPM is the 1rst difference of log (seasonally adjusted RPM) without intercept or trend. The diagnosis tests showing the ADF tests for RPM and CSI are provided in Tables D1 and D2 in Appendix D.
The ADF statistic (-13,45) for the traffic (Log(RPM)) is superior to -2,57 which is the 99% critical value, so the 1rst difference of the process is considered as stationary.
For the Current component of the CSI, namely Log (I2C), the stationary serie found is the log(I2C) with intercept and trend. The ADF statistic (-12,54) is superior in absolute value to -2,57 which is the 99% critical value, therefore the 1rst difference of the process is considered as stationary.

Figure 18: Scatter plot Log (RPM) with respect to Log (I2C)



It can be observed from a scatter plot of Log (RPM) with respect to Log (I2C) in Figure 18 that there is no clear evidence that both series are co-integrated. Therefore a co-integration test needs to be run in order to find a possible relation.
The diagnosis for the co-integration test and the Granger causality test are displayed in Table E1 and E2 in Appendix E.
Table E1 shows that there is no co-integration between both variables.
Based on the Granger test results shown in Table E2, CSI Current seems to have no causality effect on traffic evolution.

The CSI Current should have an effect with a lag of 3 or 4 months later on the RPM, as a passenger buys an air ticket on average few months before his departure.

Actually, when the CSI Current is high, air travel demand should increase in the following months. This should have a positive impact on air traffic. However, the granger causality test does not seem to confirm that intuitive assumption (as shown in the Table F1 of the Appendix F), therefore it could be helpful to check which lag seems to have the largest impact on adjusted RPM.
Based on these results the model shown in Table F2 of the Appendix F was built, showing poor statistical inferences.

Those results do not confirm the initial assumption about the potential impact of monthly values of CSI Current on monthly RPM values. Other various combinations of lags from lag 1 to 5 gave similar results leading to the same conclusion.

One explanatory variable at one time gives significant coefficients but those models of regression are statistically far worse than the autoregressive model (lag of RPM without considering CSI Current), as shown in the example of 2.

Table 2: Autoregressive models of RPM

Dependent Variable: LRPM
Method: Least Squares
Date: 02/02/00 Time: 18:23
Sample (adjusted): 1996M02 2010M12
Included observations: 179 after adjustments

	Coefficient	Std. Error	t-Statistic	Prob.
C	18.73245	0.225624	83.02508	0.0000
LI2C(-1)	-0.254234	0.049085	-5.179460	0.0000

R-squared	0.131616	Mean dependent var	17.56457
Adjusted R-squared	0.126710	S.D. dependent var	0.114497
S.E. of regression	0.106998	Akaike info criterion	-1.620909
Sum squared resid	2.026385	Schwarz criterion	-1.585296
Log likelihood	147.0714	Hannan-Quinn criter.	-1.606468
F-statistic	26.82681	Durbin-Watson stat	0.143751
Prob(F-statistic)	0.000001		

Dependent Variable: LRPM
Method: Least Squares
Date: 02/02/00 Time: 18:24
Sample (adjusted): 1996M02 2010M12
Included observations: 179 after adjustments

	Coefficient	Std. Error	t-Statistic	Prob.
C	1.148769	0.432684	2.654987	0.0087
LRPM(-1)	0.934696	0.024636	37.94031	0.0000

R-squared	0.890502	Mean dependent var	17.56457
Adjusted R-squared	0.889883	S.D. dependent var	0.114497
S.E. of regression	0.037995	Akaike info criterion	-3.691637
Sum squared resid	0.255515	Schwarz criterion	-3.656024
Log likelihood	332.4015	Hannan-Quinn criter.	-3.677196
F-statistic	1439.467	Durbin-Watson stat	2.658891
Prob(F-statistic)	0.000000		

Based on these results, it could be concluded that the consumer confidence index has a lack of significance by itself when included alone in the forecasting model.

Hence the exercise was repeated by first regressing quarterly RPM data on similar GDP data and then introducing the CSI Current.

The database lists quarterly Domestic RPMs from January 1996 to October 2010 and quarterly GDP data, representing 60 observations. The corresponding ADF tests are displayed in tables G1 and G2 of Appendix G.

Based on the ADF Unit root test the 1rst difference of Log (RPM) without neither intercept nor trend was found stationary.

As the ADF statistic (-3,6) is superior in absolute value to (-2,6) which is the 99% critical value, the 1rst difference of the process is stationary.

For the GDP series, the stationary series found is the 1rst difference of Log (GDP) with intercept.

Unsurprisingly, based on the scatter plot graph, shown in Figure 19, it is obvious that the 2 series are co-integrated.

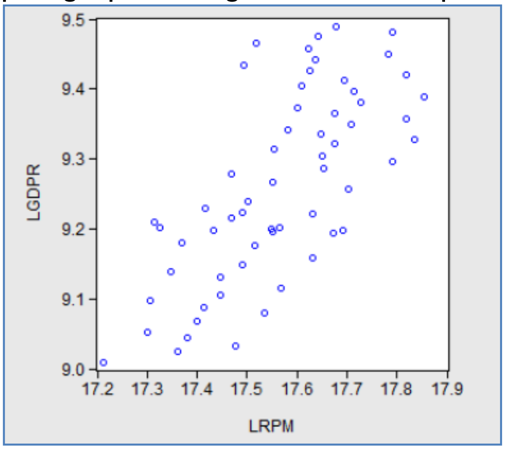
After having run several regressions on Log RPM and log GDP and its possible lags, the best model found (Model 1) is the equation (11), based on 1 lag of GDP, which is fairly typical with quarterly data:

$$\mathbf{Log(RPM_t) = 10.6347708133 + 0.749351264882 * Log(GDPR_{t-1})} \quad (11)$$

As shown in Table H1 and H2 of Appendix H, when testing the normality of the residuals and based on the Jarque Bera test result, the normality of residuals cannot be rejected.

Then based on the results of White's test (Table H3 in Appendix H) for homoscedasticity, homoscedasticity cannot be rejected.

Figure 19: Scatter plot graph of Log RPM with respect to Log RGDP



In a second step, several regressions on Log RPM and log GDP with Log CSI current and their possible lags were carried.

As the aim is to compare this new model with the previous univariate model, in order to estimate the impact of CSI Current, the same lag for GDP has been kept, and based on Akaike's Information Criterion (AIC), Schwarz and R-squared tests, the best model found (Model 2) is shown in equation (12):

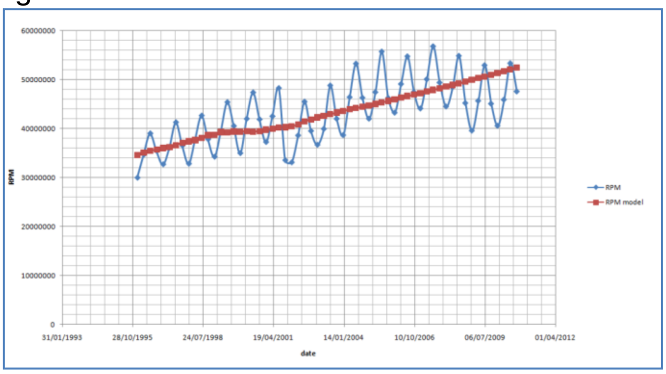
$$\mathrm{Log}(\mathrm{RPM}_t) = 5{,}712630 + 1{,}085163 * \mathrm{Log}(\mathrm{GDPR}_{t-1}) + 0{,}394514 * \mathrm{Log}(\mathrm{I2C}_{t-1}) \quad (12)$$

The statistical tests for Model 2 are shown in Appendix I.

When testing the normality of the residuals and based on the Jarque Bera test result, we cannot reject the normality of residuals.

Besides, the DW statistic is equal in this model to 1.90 which is superior to the critical value of 1.65, therefore there is no serial correlation of the residuals.

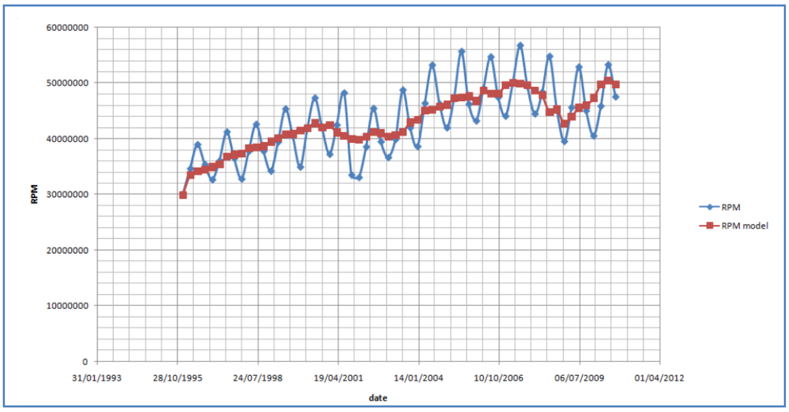
Figure 20: Actual RPM vs fitted RPM for Model 1



Then based on the results of White's test for homoscedasticity we cannot reject homoscedasticity.

The comparison of Model 1 and Model 2 is quite significant in terms of the value added by the explanatory power of the CSI Current.

Figure 21: Actual RPM vs fitted RPM for Model 2



Model 2 is showing the most significant result for the Adjusted R-squared, the AIC and the Schwarz criterion (BIC). The Adjusted R-squared has improved from 0.45 in Model 1 to 0.54 in Model 2.

Table 3: Comparison of Model 1 and Model 2 inferences tests

	Coefficient	Std. Error	t-Statistic	Prob.
C	10.63477	0.987858	10.76549	0.0000
LGDPR(-1)	0.749351	0.106700	7.022961	0.0000

R-squared	0.463893	Mean dependent var	17.57175
Adjusted R-squared	0.454487	S.D. dependent var	0.146484
S.E. of regression	0.108192	Akaike info criterion	-1.576517
Sum squared resid	0.667208	Schwarz criterion	-1.506092
Log likelihood	48.50724	Hannan-Quinn criter.	-1.549025
F-statistic	49.32199	Durbin-Watson stat	1.647686
Prob(F-statistic)	0.000000		

	Coefficient	Std. Error	t-Statistic	Prob.
C	5.712630	1.690667	3.378921	0.0013
LGDPR(-1)	1.085163	0.138023	7.862214	0.0000
LI2C(-1)	0.394514	0.114448	3.447088	0.0011

R-squared	0.557735	Mean dependent var	17.57175
Adjusted R-squared	0.541940	S.D. dependent var	0.146484
S.E. of regression	0.099141	Akaike info criterion	-1.735044
Sum squared resid	0.550418	Schwarz criterion	-1.629406
Log likelihood	54.18378	Hannan-Quinn criter.	-1.693807
F-statistic	35.31047	Durbin-Watson stat	1.906112
Prob(F-statistic)	0.000000		

Denote the AIC values of the models 1 and 2 by AIC_1=-1.58 and AIC_2 =-1.74, respectively, AIC_{min} = -1.74 is the minimum of those values. Then Exp ((AIC_{min}−AIC_1)/2) can be interpreted as the relative probability that the model 1 minimizes the estimated information loss. Then Model 1 is Exp ((-1.74−(-1.58))/2) = 0.923 times as probable as it minimizes the information loss, while the Model 2 is Exp (0) = 1 time as probable as it minimizes the information loss. In this case, Model 2 is preferred to Model 1 as it minimizes the information loss.

Given Model 1 and 2, the model with the lower value of BIC is the one to be preferred. Therefore the Model 2 showing a BIC of -1.63 is preferred to Model 1 exhibiting a BIC of -1.51.

In addition, the introduction of CSI Current in the forecasting model has significantly improved the goodness of the fit, especially in crises times, for 2001, 2008 and 2009, as it can be seen in Figure 21.

The main finding is showing that consumer confidence index is significant in-sample, and it is legitimate to check for forecasting purposes the significance of the consumer confidence index, when using real-time data. In order to investigate this potentiality, part of the annual forecasting exercise will use real-time data instead of latest available data and compare these results to the real-time annual results reported.

The impact of consumer confidence concept on air travel growth is only part of the story, as indeed the supply side offer is of particular importance to the travel decision of the potential traveller, should it be for business or for leisure purposes.

5.5. Supply side segmentation

The post-deregulation development of hub-and-spoke networks and yield management systems are the key forces behind the sustained growth of the air travel market during the cycle of economic growth in the late nineties. During this bubble economy, the dynamics of supply and demand fundamentally shifted, and a 2001 US Department of Transportation (DoT) study found clear evidence that carriers charge higher fares in the absence of effective competition.

On the other side, the simple business model developed by the so-called LCCs has allowed them to get costs down to around 40% of incumbent airlines costs (Doganis, 2001). The resulting drop in fares has resulted in the creation of new markets and traffic growing to about three times previous levels on some routes. Therefore it is necessary to specify the characteristics of each supply side segment.

5.5.1. Low Cost Carrier definition

ICAO has developed a definition of the Low Cost Carrier concept in the context of its work on liberalization of air transport regulation. In the Chapter 5.1 of the *Manual on the Regulation of International Air Transport* (Doc 9626), an LCC is defined as "*an air carrier that has a relatively low-cost structure in comparison with other comparable carriers and offers low fares and rates. Such an airline may be independent, the division or subsidiary of a major network airline or, in some instances, the ex-charter arm of an airline group.*" LCCs are also called low-cost airlines, or no-frills, discount, low-fares, budget or value-based airlines or carriers.

The ICAO definition of LCCs focuses on the aspects of costs and fares, and its criteria are similar to those adopted by the US DoT. In a 1996 report, DoT selected LCCs based on the following two quantitative elements:

a) <u>Unit operating costs:</u> Operating costs per available seat-mile for passenger service were estimated by using total operating expenses, less transport related expenses, and by using a revenue offset approach to estimate non-passenger expenses

b) <u>Pricing practices:</u> Each new entrant airline's average prices on a market-by-market basis were examined to determine whether or not the airline consistently maintains low fares relative to prices charged by other airlines before it entered a city-pair market.

In contrast, in its 2005 report, the UK CAA qualitatively identified LCCs, based primarily on whether they have a single class of travel, offer no-frills on board and are not connected to the international reservations systems. The UK CAA noted that "*the comparative lack of frills on board compared to traditional airlines has been seen, at least in the past, as one of the defining characteristics of this airline type, along with the low fares they offer. Judging whether an airline has high or low costs is both more complicated than assessing its on board services, and also potentially less relevant (if, say, an airline is pursuing a high fare market).*"

Another way to distinguish LCCs is to qualitatively examine airline business models as a whole. There is a general understanding in the industry, regulatory bodies and the media, and among the travelling public, of what a low-cost business model is and what services LCCs are supposed to offer.

That is, with some variations, point-to-point services focussing mainly on short-haul routes, high frequencies, simple fare structures, high-density single class with few or no-frills, staffing flexibility with minimal overheads, and intensive use of e-commerce for marketing and distribution. To sustain low-cost structures, these airlines usually operate a single aircraft type with higher aircraft utilization. They often use less-congested secondary airports to ensure short turn around and high punctuality and to save airport-related costs. It is the low operating costs that enable LCCs to allocate a large portion of their seats to low fares.

The identification of LCCs based on business models was adopted, *inter alia*, by the European Commission (EC), Eurocontrol, as well as the Australian Competition and Consumer Commission (ACCC) and the New Zealand Commerce Commission when they reviewed the application of Qantas and Air New Zealand for their proposed alliance.

For example, the EC report divided airlines into four categories: full service network carriers, LCCs, regional carriers and holiday/charter carriers. The LCCs category comprises "*those airlines that offer low prices for the majority of flights and which mainly operate on short and medium-distance routes with low overheads and a relatively high load factor*".

In choosing the appropriate selection method amongst the ones described above, a trade-off between the limitation of data and the application of an element of subjective judgement should be taken into consideration.

On the one hand, the quantitative assessment of both costs and fares could produce the most accurate list of LCCs with minimum room for subjective judgement. It is, however, very hard to monitor air fare movements on a market-by-market basis and also to know how many seats are allocated to low fares, due to the lack of readily available data. On the other hand, the qualitative assessment of either on board services or business models could be more practical given readily available information, although a high degree of subjective judgement might be involved. As the number of LCCs is growing, more variants will emerge among LCCs that differentiate their quantity and quality of services, thereby increasing the impact of subjective judgement on the selection process.

Based on the regional LCCs table provided by ICAO on its site, the list of the US LCCs taken into consideration for this study is in Table 4, restricted however to the airlines showing enough historical data and therefore excluding for instance Virgin America, as well as the ones that have bankrupted such as Independence Air (2006) or ATA, or which have merged under a new branding not recognized as an LCC one, such as America West.

Table 4: US LCCs start year of operation

Airline	Start year
JetBlue Airways	1998
Southwest Airlines	1967
Spirit Airlines	1980
AirTran Airways	1992
Allegiant Air	1997
Frontier Airlines	1994

Source: ICAO

Although Southwest and Air Tran merged end 2010, their traffic are shown separately.

5.5.2. The different business models

Much has been written on whether the network carriers'hub model has a future or not, in terms of cost reduction facing, point-to-point business model.

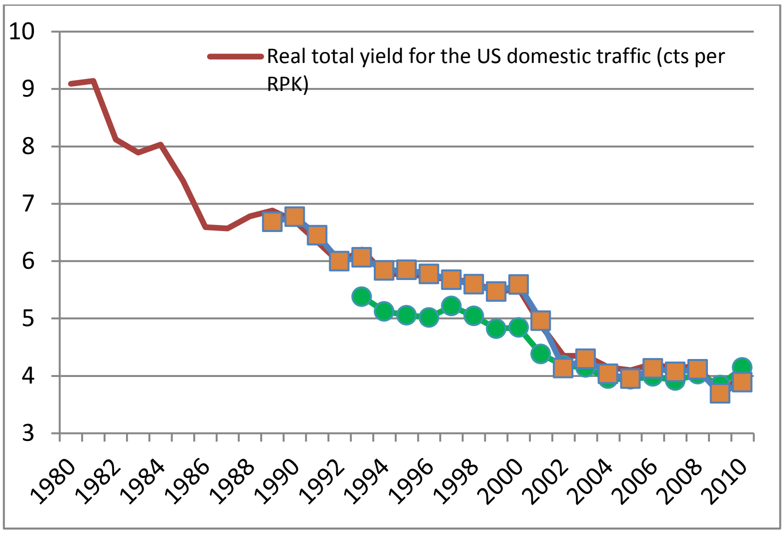
Bruecker et Al (1992) found evidence of the importance of networks in reducing costs. For example, the airfare in one market may be correlated with the airfares in other markets sharing one common end point. This phenomenon, called network autocorrelation (Black, 1992) has been recognized and studied for years (Cliff and Ord,1973, 1981; Goodchild, 1987; Griffith, 1987). Legacy airlines network are typically applying this network correlation through their hub and spokes network.

In parallel, the new paradigm settled by LCCs is built on low cost/low fares business model outside a network context, making the network autocorrelation not relevant for LCCs supposed to offer point-to-point services associated to lower fares leading to a higher traffic growth.

As shown in Figure 22, between 2000 and 2010 the yields of the LCCs, expressed in real values, decreased by 1.5% per year (from a lower basis), while during the same period the real total yields for the whole US domestic market and the legacy carriers decreased respectively by 3.1% and 3.6% per year. It is noteworthy that as the traffic operated by Southwest has represented in average 48% of the traffic operated by the LCCs in the last 15 years, Southwest´s yields have been taken as representatives of the LCCs ones.

Regarding the legacy yields, they have been calculated based on the ones of United Airlines, American Airlines, Continental, Delta Airlines, Northwest, Alaska Airlines and US Airways.

Figure 22:.Real Yields evolution for the US Domestic air travel market



Source: Airlines For America (A4A) site, ICAO

In 2005, the LCCs' market share (as highlighted in grey in Table 5) measured in terms of passengers enplaned was only 19% of the total US domestic traffic. Five years later, this market share has increased by five points to reach 24%, notwithstanding that America West, rebranded as US airways after their merger, is not taken into account as an LCC.

Table 5: Market shares of the Top ten airlines in the US Domestic market

2010 Rank	Carrier	2010 Passengers (Mill)	Market share of the total Domestic US market	2005 Rank	Carrier	2005 Passengers (Mill)	Market share of the total Domestic US market
1	Southwest	106	17%	1	Southwest	88	13%
2	Delta*	90	14%	2	Delta	78	12%
3	American	66	10%	3	American	77	11%
4	US Airways	45	7%	4	United	55	8%
5	United	43	7%	5	Northwest	47	7%
6	Continental	31	5%	6	US Airways	37	6%
7	AirTran	24	4%	7	Continental	33	5%
8	SkyWest	23	4%	8	America West	21	3%
9	JetBlue	21	3%	9	American Eagle	17	3%
10	American Eagle	15	2%	10	AirTran	17	3%
Top Ten total			72%	Top Ten total			70%

* Delta's 2010 number is the report of the merged Delta and Northwest.

Source: BTS

The rise of the low cost airlines has led to the practice of splitting the industry into what are called "Legacy", "Low Cost" and "Regional" airlines with membership in each group determined not by total revenue but by the operating nature of the carrier. In the context of this study the DoT method of grouping carriers by Majors, Nationals, Large Regionals and Medium (defined by total annual revenue) will not be followed.

The industry traffic data classification is more adapted to our statistical analysis. Thus some Major airlines, such as Southwest, are now in the Low Cost group while other Majors, such as American Eagle, are in the Regional group regrouping all the regional carriers.

Besides, as shown in Table 6, the Average Annual Growth Rates (AAGR) for passenger traffic registered in the last ten years by the legacy airlines and the LCCs or the regional carriers are substantially different. The consumption pattern is thus different and the Consumer Confidence Index associated to the fare effect on the traffic growth may play a different role

Table 6: 2000-2010 traffic*, market share and growth of US carriers

Year	Total traffic Domestic US	US LCCs traffic	LCCs Market Share	Legacy traffic Domestic US	Legacy Market Share	Regionals traffic Domestic US	Regionals Market Share
2000	818	144	18%	592	72%	65	8%
2001	773	150	19%	545	71%	66	9%
2002	756	155	20%	533	70%	68	9%
2003	805	191	24%	535	66%	78	10%
2004	888	217	24%	570	64%	101	11%
2005	933	239	26%	578	62%	115	12%
2006	942	253	27%	563	60%	126	13%
2007	972	269	28%	569	58%	128	13%
2008	934	234	25%	559	60%	125	13%
2009	883	244	28%	520	59%	119	13%
2010	905	261	29%	518	57%	125	14%
AAGR 2000-2010	1%	6%		-1%		7%	

*Traffic is expressed in Billions RPKs *Source: BTS and ICAO*

In light of the above, it is confirming why it is necessary to model air travel demand according to the supply segments. However there is a tight link between legacy carriers and regional ones, as a great majority of regional airlines are privileged partners (fully owned, code-sharing, franchisees, etc..) of some legacy airlines.

Table 7: Links between Legacy and the main Regional airlines

Main regiional airlines
Mesa Airlines
SkyWest Airlines Atlantic Southeast Airlines Express Jet
Pinnacle airline Mesaba airline
Air Wisconsin (US airways express)
Horizon air
American Eagle
Comair

Legacy airlines	Affiliated regional
American Airlines	American Eagle Airline
Delta Airlines/Northwest	Comair
United Airlines Continental Airlines	United Express, Continental Express Continental Connection
US Airways	Air Wisconsin
Alaska Airline	Horizon Air

Source: BTS

Therefore it is difficult to separate the origin of the traffic between legacy Carriers and regional airlines, and for the purpose of this study these two traffics will be combined under the label of network carriers.

For comparison purposes, and in order to identify more clearly the fare effect on the traffic growth, in the different supply segments, the analysis of the data will start only in 1995, the year where valuable data for LCCs traffic and yields have started to be available.

As shown in section 5.1, when modelling traffic in global in the US domestic market, it appears obviously as a maturing market: the income elasticity is dropping from 2.2 in the 70-80 decade to 1.2 in the 2000-20010 decade.

Then going through the supply side demand modelling, and as reflected in equation (13), it appears that the income elasticity for the traffic carried by the legacy carriers is estimated at 0.8 between 1995 and 2010 which is representing a very mature market in the legacy segment.

Domestic US Legacy:

LnRPK= -2.5+0.8 LnRGDP/Cap (13)

Table 8: Model specifications for Legacy carriers between 95 and 2010

Variable: Log RPK Legacy 95-2010	**Parameter Estimate**	**Standard Error**	**Type II SS**	**F Value**	**Pr > F**
Intercept	-2.51559	1.15336	0.00534	4.76	0.0467
LogRGDPCAP	0.84620	0.10887	0.06779	60.42	<.0001
Root MSE	0.03350	R-Square	0.8119		
Dependent Mean	6.44894	Adj R-Sq	0.7984		
Coeff Var	0.51942				

In the Low Cost Carriers segment the income elasticity is above the 70-80 decade for the global traffic at 4.3, as reflected in the modelling equation (14). it is clearly a non-mature market very price-elastic, showing that there was a non-satisfied demand in the past.

Domestic US LCCs::

*LnRPK=--34+**4.3** LnRGDP/Cap**-1.1** LnReal Fares* (14)

Table 9 : Model specifications for LCCs

Variable: Log RPK LCC 95-2010	**Parameter Estimate**	**Standard Error**	**Type II SS**	**F Value**	**Pr > F**
Intercept	-34.57366	3.59761	0.26663	92.36	<.0001
LnReal Fares	-1.09165	0.21363	0.07539	26.11	0.0002
LogRGDPCAP	4.31864	0.25010	0.86081	298.17	<.0001
Root MSE	0.05373	R-Square	0.9861		
Dependent Mean	5.10266	Adj R-Sq	0.9840		
Coeff Var	1.05299				

In terms of market typology, taking into account that a general rule of thumb is stating that price elasticities are around 1.3 in leisure markets and 0.2 in business markets, it seems that in liberalised markets like Domestic USA or Intra-Europe the traditional demand segmentation (business vs leisure) is becoming less significant than the supply segmentation, namely traditional network carrier and Low Cost Carrier in both Domestic USA and Intra-Europe, with an additional differentiation for Charters in the European market.

5.6. Models, forecasts and results

In a previous paragraph it has been checked that the consumer confidence indices cannot establish better forecasts as only explanatory variables introduced in a monthly time series analysis of the Domestic US air travel market. However, when modelling the quarterly traffic with the GDP as first regressor, it appeared that if it is improving the forecast accuracy of the model, notably in crisis time, when including them as a second regressor.

Therefore the aim is to determine if annual short-term forecasts in crisis time can be improved by including consumer confidence indices, before reverting to the long-term trend established before crisis.

5.6.1. The data series

After the worldwide oil crisis and the Airline Deregulation Bill, there are strong reasons to believe that the relationship between traffic, airfares and income has not been the same after and before 1978. Moreover, the number of operators have been really stabilized only starting from 1985, which explains the reason why the historical data series considered in this study for the global domestic US traffic are starting from 1985. Air traffic data are extracted from the US DoT Form 41, before being segmented as described in the previous paragraph. Besides, as said before the regression analysis of the Legacy and LCC data series will start only in 1995, the year where valuable LCCs data have started to be available.

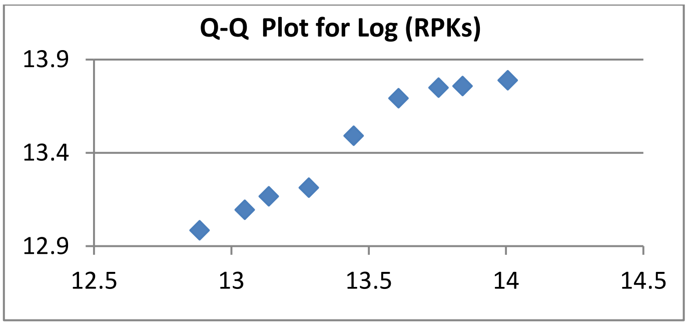
5.6.2. The OLS regressions during the 1985-2010 time span

The preliminary step is to test the RPKs series from 1985 to 2010 using currently known regressors values in order to determine if the Consumer Confidence Index has any explanatory power in air traffic growth, before applying it for forecasting purposes in real time.

The first step is to determine normality of variables and the Shapiro-Wilk (W) statistic is close to one for this Log (RPK) analysis between 1985 and 2010, thus indicating normality. The p-value is greater than 0.05, then the null hypothesis has not been rejected, which is the case for this model, as shown in the statistical tables for this model in Appendix J.

The Q-Q plots is showing an approximate line in the plot, as displayed in Figure 23.

Figure 23: Q-Q plot for Log (RPK 85-2010)



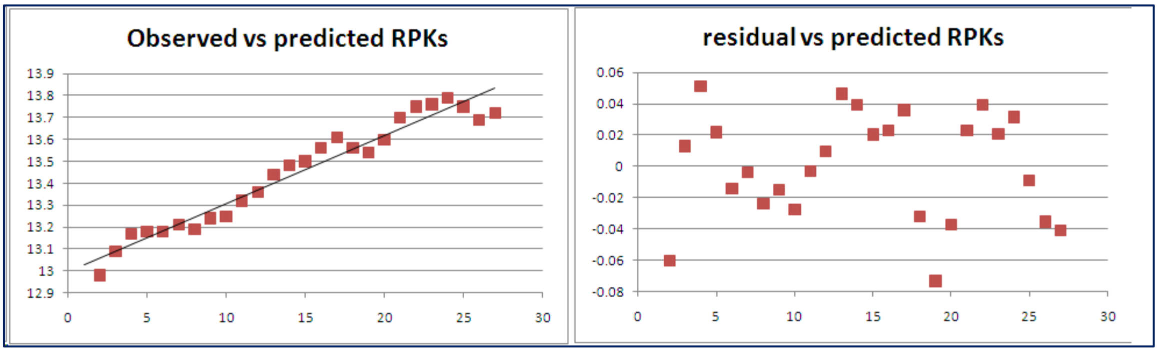
As discussed in Section 4.4, It is important to maintain a large number of observations, substantially exceeding the number of regressors used in the regression.

In this specific case, showing 26 observations, the limit fixed for an acceptable model is 2 regressors. Based on the Log RPKs series going from 1985 to 2010 the following potential regressors (expressed in Log values) are introduced in the stepwise regression: RGDP/Cap, RGDP, RU and Real yields.

The best initial model found, Model 1, is based on Real GDP without any other explanatory variable, as shown in the table K1 of Appendix K, while the residuals and the predicted values for Log(RPK 1985-2010) are in table K2. After having screened the data for potential errors, there is a need to focus on regression diagnostics to verify whether the model meets the assumptions of linear regression. The next step is to check any misspecification of the model by applying diagnostic tests on the four principal assumptions which justify the use of linear regression models for purposes of prediction.

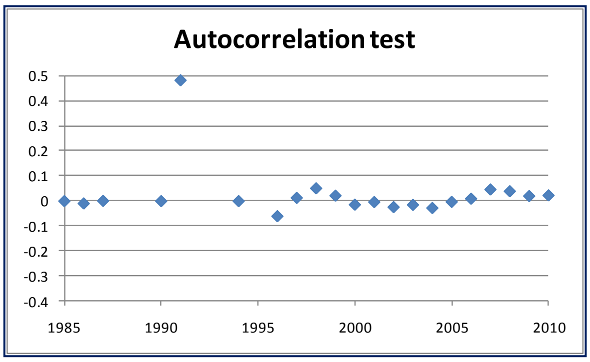
For the linearity tests, the points should be symmetrically distributed around a diagonal line in the plot of the *observed versus predicted values* or around a horizontal line in the of *residuals versus predicted values*, as it is the case for this RPK regression, according to the graphs of Figure 24.

Figure 24: Linearity tests for Model 1 of Log (RPK 85-2010)



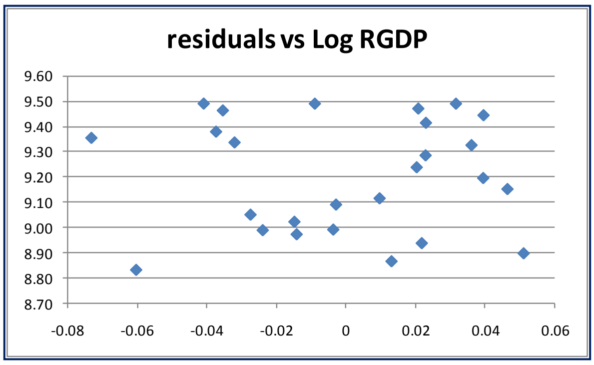
For the autocorrelation test most of the residual autocorrelations should fall between - 0.4 and +0.4, as the sample size is 26, as shown in Figure 25 featuring the autocorrelation test for Model 1.

Figure 25: Autocorrelation test for Model 1 of Log (RPK 85-2010)



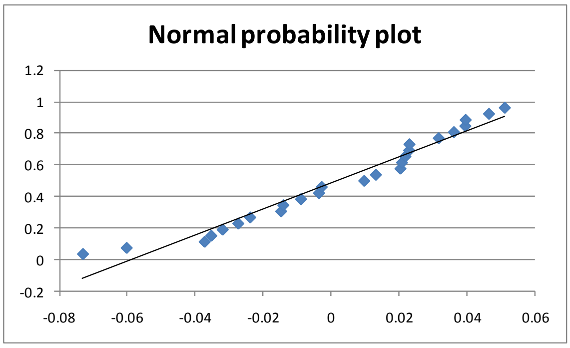
Regarding the homoscedasticity assumption, the plots of *residuals versus time* and *residuals versus predicted value of Log RPK* are showing no evidence of residuals that are getting larger either as a function of time or as a function of the predicted value of Log RPK. The same pattern (Figure 26) is shown when plotting residuals versus the independent variable, namely Log RGDP.

Figure 26: Homoscedasticity test for Model 1 of Log (RPK 85-2010)



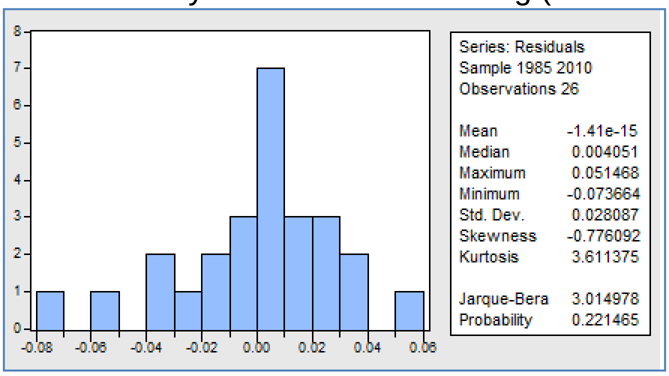
When testing the normality of the error distribution, and as expected from points coming from a normal distribution, the normal probability plot is producing an approximately straight line, as shown in Figure 27.

Figure 27: Normal probability scatter plot for Model 1 of Log (RPK 85-2010)



In Figure 28, this result is confirmed by the Jarque-Bera statistic showing that residuals are normally distributed with 95% of confidence.

Figure 28: Normality test for Model 1 of Log (RPK 85-2010)



Finally when looking at influential points, a general cutoff to consider is 2 and the DFFITS for this regression (Table 10) is showing no influential point.

Table 10: Test for influential points for Model 1 of Log (RPK 85-2010)

YEAR	student_Log RPK	rstudent_Log RPK	DFFITS_Log RPK
1985	-1.8843	-1.9984	-0.8446
1986	0.40323	0.39608	0.15431
1987	1.56088	1.61203	0.58165
1988	0.65838	0.65042	0.21237
1989	-0.4264	-0.419	-0.1253
1990	-0.1101	-0.1078	-0.0308
1991	-0.7169	-0.7095	-0.2037
1992	-0.4418	-0.4342	-0.1148
1993	-0.8139	-0.808	-0.1998
1994	-0.0852	-0.0834	-0.0189
1995	0.28362	0.27812	0.06027
1996	1.36232	1.3884	0.28578
1997	1.15644	1.16502	0.23317
1998	0.59586	0.58768	0.11908
1999	0.67252	0.66465	0.14245
2000	1.0644	1.06749	0.24665
2001	-0.9475	-0.9454	-0.2235
2002	-2.1687	-2.3677	-0.5826
2003	-1.1109	-1.1166	-0.2912
2004	0.68645	0.67869	0.19291
2005	1.18871	1.19953	0.36762
2006	0.62839	0.62028	0.20309
2007	0.9606	0.95899	0.32943
2008	-0.2731	-0.2678	-0.092
2009	-1.07	-1.0734	-0.345
2010	-1.2447	-1.2599	-0.4332

Based on this model 1 and leaving in the stepwise process the other variables, namely Real yields and RU, the various confidence indices CCI, CSI, CSI Current and CSI Expected are introduced in the stepwise box. The stepwise procedure produced the following model (Model 2) showing that besides Log RGDP, only Log CSI Current has appeared as significant enough to enter the equation.

Table 11: Specifications of Model 2 of Log (RPK 85-2010)

Variable: Log RPK 85-2010	Parameter Estimate	Standard Error	Type II SS	F Value	Pr > F
Intercept	2.50313	0.38909	0.03549	41.39	<.0001
Log RGDP	1.10981	0.02791	1.35588	1581.28	<.0001
LnCSI Curr	0.15828	0.04825	0.00923	10.76	0.0033

For the variable GDP a positive sign is correctly calculated since an income increase is expected to have a positive influence on traffic growth, while similarly, for the variable Confidence a positive correlation sign is correctly calculated since an increase in consumer confidence is expected to have a positive influence on air travel demand.

A prerequisite for the use of independent variables in a model is to test the absence of high correlation between these 2 regressors. Table 12 presents the correlation matrix of the variables of the model, as well as the Variance Inflation.

Table 12: Correlation matrix of the regressors for Model 2 of Log (RPK 85-2010)

Correlation of Estimates				
Variable: Log RPK 85-2010	**Intercept**	**Log RGDP**	**LnCSI Curr**	**Variance Inflation**
Intercept	1	-0.8404	-0.7794	0
Log RGDP	-0.8404	1	0.3157	1.11071
LnCSI Curr	-0.7794	0.3157	1	1.11071

In this case VIF is close to 1 which excludes any potential collinearity.

The choice of a model depends on the study's objectives, hence it is useful to compare the significance tests of each of these 2 models, the Model 1 (including only RGDP as regressor) with Model 2 (including both RGDP and CSI Current as regressors), before evaluating their forecast errors.

Based on the comparisons tables L1 and L2 in Appendix L, the first conclusions are showing that in both models 1 and 2 the F-test has a satisfactory value, while the value of the adjusted R-Squared has improved in Model 2. A higher R-squared is relevant as the objective is to get a more accurate predicted value and not necessarily to assess the relationship between variables,. As the RMSE in Model 2 has decreased by 16%, it indicates a better fit for the Model 2.

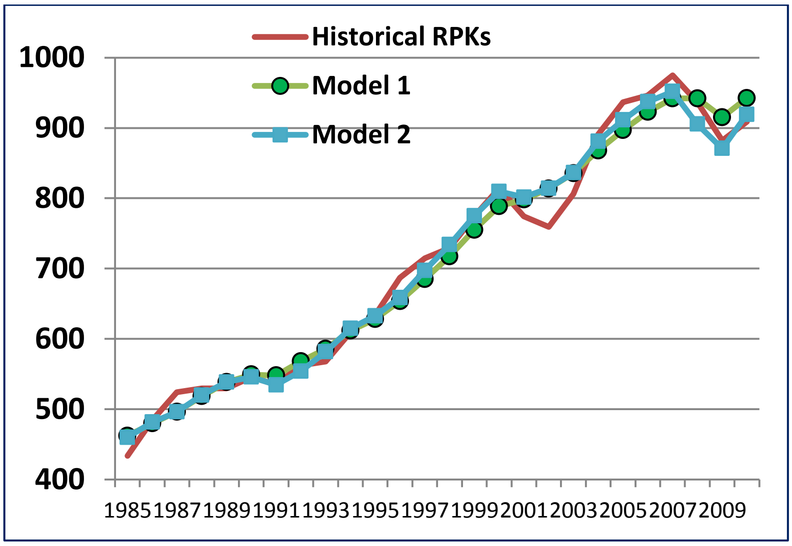
Going further in the compared analysis of the two models, additional statistical tests have been computed, as shown in the tables of Appendix M.

When looking at the Mallow's C_p statistic (C(p)), the 2 models perform equally, while Model 2 is showing the smallest value of AIC and the BIC in the Model 2 is still lower than in Model1, allowing to conclude that there is no over fitting. Finally the Sum of Square Error (SSE) has decreased in Model 2, indicating a best fit line.

The parameter estimate for RGDP does not change significantly which means that the income elasticity is at the same level at an average of 1.1. The t value is higher for RGDP in the second model while significant enough for the variable CSI Current.
The various sets of diagnostic tests are showing that the Model 2 including the confidence index performs better than the Model 1.

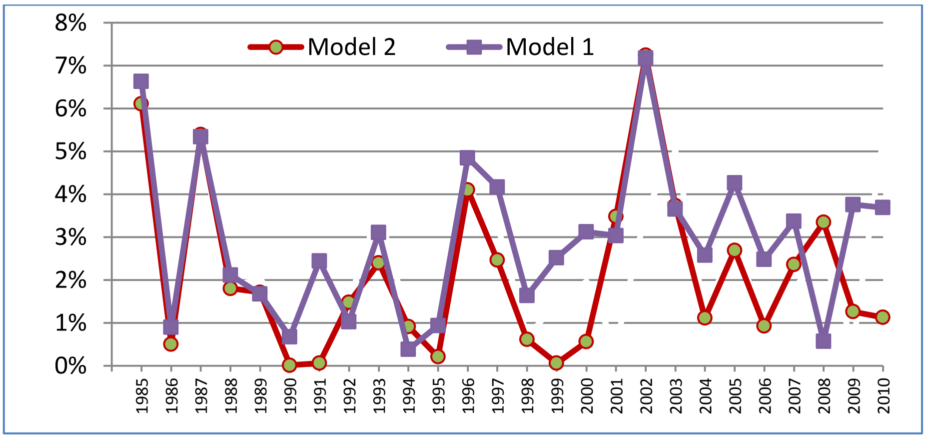
The model 2 is showing the best goodness of the fit especially in 1991 and 2009, while the forecasting error in absolute value is in general lower in Model 2 (represented with a circle marker in Figure 30), notably during the crises years, except for the year 2008.

Figure 29: Goodness of the fit between Model 1 and 2 for Log (RPK 85-2010)



Most forecasters know that during crisis time it is useful to use dummies to find a better fit of the regression equation. Therefore, it is useful to model the historical RPKs with RGDP (Model 1) and dummy variables equal to 0 for all the years except for 1991, 2001, 2002, 2008 and 2009 where the dummy variables were equal to 1, in order to check if the confidence index has an added value compared with this common practice.

Figure 30: Absolute values of the forecast errors of Model 1 and 2



Indeed, dummy variables may be used to indicate the occurrence of wars, or major crises. Thus, it could be thought of as a truth value represented as a numerical value 0 or 1.The addition of dummy variables always increases model fit (coefficient of determination), but at a cost of fewer degrees of freedom and loss of generality of the model. Too many dummy variables result in a model that does not provide any general conclusions.

When introducing the dummy variable with the RGDP and the CSI Current as potential variables in the stepwise regression, the first finding is showing that the dummy is not significant enough to enter the model. Therefore CSI Current is retired from the potential regressors.
The results of this regression, called Model 3 are shown in the tables of Appendix N.
The RMSE is still lower in Model 2, while Adjusted R^2 is still higher in Model 2. In addition AIC, BIC and SBC are still lower in Model 2.

Finally, it is noteworthy that between Model 1 and Model 3, the t-value of the parameter estimate of RGDP has been divided by 2, while there are fewer degrees of freedom, 4 in Model 3 compared to 5 in Model 2.

For checking purposes, regarding the inclusion of confidence as an explanatory variable, additional tests need to be computed on Model 2, related to the exogeneity of the regressors as well as to the structural stability of this model. In order to run the exogeneity test, a t-test on the mean of the errors is calculated in equation (15) based on the number of observations which is 26.

$$t = \frac{1{,}41 * 10\char`^(-15)}{0{,}028087} = 5{,}02 * 10^{-14} \ll \ t_{95\%}(n-2) = 2{,}064 \qquad (15)$$

The strict exogeneity of the residuals cannot be rejected.

In order to test the structural stability at a break point assumed to be at the year 2000, a Chow test is conducted.

Table 13: Chow test for structural stability of Model 2 for Log (RPK 85-2010)

Chow Breakpoint Test: 2000
Null Hypothesis: No breaks at specified breakpoints
Varying regressors: All equation variables
Equation Sample: 1985 2010

F-statistic	2.210102	Prob. F(3,20)	0.1185
Log likelihood ratio	7.444259	Prob. Chi-Square(3)	0.0590
Wald Statistic	6.630307	Prob. Chi-Square(3)	0.0847

The null hypothesis that there are no structural breaks in 2000 cannot be rejected, hence the model is valid for the whole sample period.
In order to confirm this result, the data are split into two sub-periods, one from 1985 to 2000 and the other from 2000 to 2010, and 2 regressions are estimated for each sub-period separately, in addition of the regression already estimated for the whole period from 1985 to 2010. The restricted regression is now the regression for the whole period (Model 2) while the unrestricted regression comes into two parts, one for each of the subsamples: Model 2bis

and Model 2Ter. Since the number of restrictions is equal to the number of coefficients that are estimated for each of the regression, the number of regressors in the unrestricted regressions is 4.

Table 14: Specifications of Model 2bis and Model 2ter for Log (RPK 85-2010)

Sample: 1985 2000
Included observations: 16

	Coefficient	Std. Error	t-Statistic	Prob.
C	2.241249	0.454248	4.933971	0.0003
LOG_RGDP	1.133552	0.051023	22.21640	0.0000
LNCSI_CURR	0.169156	0.094368	1.792519	0.0963

R-squared	0.981971	Mean dependent var	13.29804
Adjusted R-squared	0.979197	S.D. dependent var	0.177919
S.E. of regression	0.025662	Akaike info criterion	-4.320263
Sum squared resid	0.008561	Schwarz criterion	-4.175403
Log likelihood	37.56211	Hannan-Quinn criter.	-4.312845
F-statistic	354.0217	Durbin-Watson stat	1.414002
Prob(F-statistic)	0.000000		

Sample: 2000 2010
Included observations: 11

	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.219088	1.703925	-0.715459	0.4947
LOG_RGDP	1.480127	0.162328	9.118147	0.0000
LNCSI_CURR	0.208333	0.064307	3.239668	0.0119

R-squared	0.915647	Mean dependent var	13.67693
Adjusted R-squared	0.894559	S.D. dependent var	0.086096
S.E. of regression	0.027957	Akaike info criterion	-4.089297
Sum squared resid	0.006253	Schwarz criterion	-3.980780
Log likelihood	25.49114	Hannan-Quinn criter.	-4.157702
F-statistic	43.41968	Durbin-Watson stat	1.448646
Prob(F-statistic)	0.000051		

The test is in equation (16) comparing RSS1 (Model 2 is the restricted regression) to the sum of the residual sum of squares for the two sub-samples, RSS2 + RSS3 of the 2 unrestricted regressions (Model 2bis and Model 2ter).

$$Chow = \frac{(0{,}019721-0{,}008561-0{,}006253)/_{3}}{(0{,}008561+0{,}006253)/_{(26-6)}} = 2{,}208 \qquad (16)$$

$$2{,}208 < F_{3,20}(95\%) = 3{,}10 \qquad (17)$$

As shown in equation (17), the F value for the Chow test is lower than the critical value for F (3, 20) which is 3.10. Therefore the Null hypothesis cannot be rejected and it can be concluded that the Model 2 including the CSI Current as regressor, is stable over all the sample period.

5.6.3. The OLS regressions in the 1985-2000 time span

The first sets of data used are based on the period going from 1985 to 2000, in order to check if including real-time forecasts for all regressors is giving more significant traffic forecasts when compared to actual values from 2001 to 2010.

It is necessary to test real-time macroeconomic data, as opposed to the data available in today's data bank, as we wish to investigate whether consumer confidence would help us increase forecast accuracy. If data revisions for both economic variables and confidence indices were small and inconsequential, there would be no need to use real-time data.

The variables taken into account are the Napierian logarithm (Log or Ln) of the real value of the GDP/Capita (LogRGDP/Cap) as representative of the annual household income, the real yields (LogRYields) for the whole Domestic US market (from 1985 to 2010), but also for the legacy carriers (LogRLegYields) and for the LCCs ones (LogRLCCYields), starting only from 1995. Besides a valuable real fares data series has also been introduced (LogRfares) starting also from 1995, as well as the Rate of Unemployment (LogRU), in addition of the inflation index rate (Log CPI), although the inflation effect is already taken into account in the real measures of either GDP or yields.

In the stepwise procedure Log RGDP 2000, Log RGDP/Cap 2000, Log RU 2000 and Log RYields 2000 are initially included. The best initial model found is based on Log RGDP 2000 and it will be referred to as Model 1. When introducing the confidence variables in the stepwise (without choosing any index in particular, including the current and the expected values of the indices), the CSI current appeared as significant enough to enter the new model, Model 2, showing a slight improvement in the Adjusted R^2 value and a decrease in the RMSE. The stepwise results for these 2 models are shown in Appendix O. Based on the economic forecasts established by Global Insight in 2000 for both RGDP and CSI Current, the out-of sample data for 2001 to 2010 built from respectively Model 1 and Model 2 are showing significant more accurate forecasts during crisis times, notably in 2001, 2002, 2003, 2008 and 2009, as highlighted in grey in Table 15.

Table 15: Comparison of forecast errors for Model 1 and 2 for Log (RPK 85-2000)

Year	Historical RPKs 1985-2000	Model 1	Model 1 Forecast Error	Model 2	Model 2 Forecast Error
1985	434	453.4	**5%**	457.4	**5%**
1986	484	472.5	**2%**	479.8	**1%**
1987	524	492.2	**6%**	496.3	**5%**
1988	530	517.5	**2%**	522.2	**1%**
1989	530	539.9	**2%**	541.8	**2%**
1990	546	551.6	**1%**	548.5	**1%**
1991	535	548.4	**3%**	535.3	**0%**
1992	562	569.0	**1%**	553.8	**2%**
1993	568	587.5	**3%**	581.8	**2%**
1994	609	616.7	**1%**	616.7	**1%**
1995	634	637.0	**0%**	637.0	**0%**
1996	687	665.0	**3%**	663.6	**3%**
1997	715	701.2	**2%**	704.7	**1%**
1998	729	738.2	**1%**	743.4	**2%**
1999	775	775.7	**0%**	781.4	**1%**
2000	814	811.5	**0%**	815.0	**0%**
2001	775	814.0	**5%**	798.6	**3%**
2002	759	838.4	**10%**	818.0	**8%**
2003	806	869.8	**8%**	847.0	**5%**
2004	891	920.2	**3%**	906.6	**2%**
2005	937	963.5	**3%**	948.2	**1%**
2006	946	1002.3	**6%**	983.5	**4%**
2007	975	1043.5	**7%**	1016.0	**4%**
2008	937	1079.3	**15%**	995.4	**6%**
2009	882	1116.7	**27%**	1018.8	**15%**
2010	909	1155.0	**27%**	1079.3	**19%**

Besides, while the two models perform more or less equally in normal times before 2000, Model 2 seems to give a lower forecast error in the last decade should it be in normal or crises times. The consumer confidence seems to have an explanatory power in the presence of macroeconomic variables.

5.6.4. The OLS regressions in the 1985-2007 time span

The second step is to evaluate the out-of-sample data for 2008, 2009 and 2010, by modeling the traffic from 1985 to 2007, following the same process than the one adopted for the data series from 1985 to 2000, in order to compare the real values with the forecasts obtained for 2008, 2009 and 2010. In the stepwise procedure Log RGDP 2007, Log RGDP/Cap 2007, Log RU 2007 and Log RYields 2007 are initially included. The best initial model found is based on Log RGDP 2007 and it will be referred to as Model 1. When adding the confidence variables, the CSI current was chosen through the stepwise process to be introduced in the equation and the new model, Model 2, appears more significant with a slight improvement in the Adjusted R^2 value, showing an increment to the goodness of fit of Model 2 vs Model 1 and a decrease in the RMSE. The stepwise results for both models are shown in Appendix P. Then when looking at the change in significance statistics (t, F) tests resulting from the addition of the confidence indices to the equation, both of them have been improved.

Table 16: Comparison of forecast errors or Model 1 and 2 for Log (RPK 85-2007)

Year	**Historical RPKs 1985-2007**	Model 1	**Model 1 Forecast Error**	Model 2	**Model 2 Forecast Error**
1985	434	486	**12%**	461	**6%**
1986	484	499	**3%**	486	**0%**
1987	524	524	**0%**	499	**5%**
1988	530	541	**2%**	524	**1%**
1989	530	545	**3%**	541	**2%**
1990	546	527	**3%**	545	**0%**
1991	535	545	**2%**	527	**2%**
1992	562	579	**3%**	545	**3%**
1993	568	616	**8%**	579	**2%**
1994	609	635	**4%**	616	**1%**
1995	634	660	**4%**	635	**0%**
1996	687	704	**2%**	660	**4%**
1997	715	741	**4%**	704	**2%**
1998	729	781	**7%**	741	**2%**
1999	775	810	**5%**	781	**1%**
2000	814	786	**3%**	810	**0%**
2001	775	794	**2%**	786	**1%**
2002	759	817	**8%**	794	**5%**
2003	806	875	**9%**	817	**1%**
2004	891	911	**2%**	875	**2%**
2005	937	945	**1%**	911	**3%**
2006	946	965	**2%**	945	**0%**
2007	975	983	**1%**	965	**1%**
2008	937	1007	**8%**	983	**5%**
2009	882	1035	**17%**	1007	**14%**
2010	909	1087	**20%**	1035	**14%**

Based on the economic forecasts established by Global Insight in 2007 for both RGDP and CSI Current, the out-of sample data for 2008 to 2010 built from respectively Model 1 and Model 2 are showing significant more accurate forecasts during crisis times, notably in 2008 and 2009, as well as in 2010, as highlighted in grey in Table 16. More generally speaking, the model 2 is performing better than model 1 between 2000 and 2010, when plotting the estimated results vs the real traffic registered between 2000 and 2010.

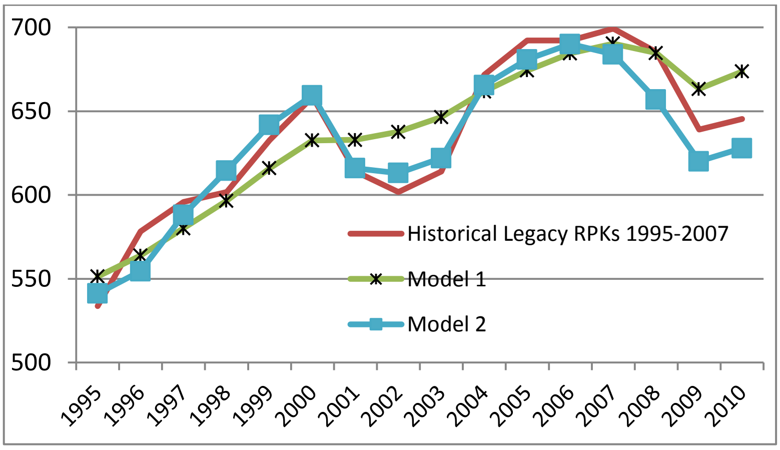
5.6.5. The OLS regressions in the 1995-2007 time span for the supply side

The next step is to assess the sum of each model built for each supply segment, in order to compare it with the global one, both of them built from 1995 to 2007, for comparison purposes. The objective is to check if the out-of-sample data produced for 2008, 2009 and 2010 are more accurate when including the confidence index in the top down model or in the bottom-up one. It would have been also relevant to do the same for the 1995 to 2000 period, but the data sample is too small to enable any validation of the results.

The results for the legacy segment, displayed in Table Q1 of Appendix Q, indicate that model 2 including CSI Current perform better than model 1 that does not include confidence indicator. When looking at the forecasting errors the forecasts have been improved notably during the crisis time, but also during normal periods, the exception of 2000 and 1996 correspond to high traffic growth.

The model including the CSI Current has shown the same noticed improvements in the previous modelling, namely improvement of the adjusted R-Squared and decrease of RMSE, as well as improvement in the t-value of the main explanatory variable, Log RGDP/Cap 95-07.

Figure 31: Goodness of the fit between Model 1 and 2 for Legacy carriers



Once again, as shown in Figure 31, the goodness of the fit of the model is significantly improved by adding the consumer confidence, notably during crisis times, while the out-of-sample data are more accurate when compared to real values of 2008, 2009 and 2010.

The same process was applied to the LCC segment, by introducing the confidence elements in the initial forecasting equation based on LogRGDP95-07 and LogRLCC Yields 95-07 with the main results shown in Appendix R.

Regarding the assumption on LCC yields decrease between 2007 and 2010 a decrease of 1% per year has been decided, based on the 2.1% average annual yield decrease registered between 1995 and 2007, which represents more than what really occurred, estimated at 0.5% p.a. from 2007 to 2010.

Table 17: Comparison of forecast errors for Model 1 and 2 for LCCs

Year	**Historical LCCs RPKs**	Model 1	**Model 1 Forecast Error**	Model 2	**Model 2 Forecast Error**
1995	80	78	**2%**	79	**1%**
1996	89	87	**3%**	86	**4%**
1997	95	93	**2%**	92	**3%**
1998	101	107	**6%**	107	**7%**
1999	124	126	**1%**	128	**3%**
2000	144	139	**4%**	139	**3%**
2001	150	157	**4%**	155	**3%**
2002	155	171	**11%**	170	**10%**
2003	191	184	**4%**	182	**5%**
2004	217	210	**3%**	219	**1%**
2005	239	227	**5%**	236	**1%**
2006	253	240	**5%**	245	**3%**
2007	269	257	**5%**	258	**4%**
2008	233	258	**11%**	253	**9%**
2009	245	243	**0%**	237	**3%**
2010	262	263	**0%**	254	**3%**

The improvements seen with Model 2 compared to Model 1 are not spectacular as indeed the initial model was already showing a very goodness of the fit. The introduction of confidence index has marginally improved the forecast error in 2001, 2002 and 2008.

This matter of fact is clearly showing that the air travel demand for the LCC seems much more sensitive to the price than to confidence sentiment, at the opposite of the demand for the Legacy segment.

Table 18: Comparison of CSI actual values and forecasts issued in 2007

Year	**CSI Actual values**	**CSI Forecasts in 2007**
2007	85.6	85.6
2008	63.8	87.1
2009	66.3	86.4
2010	71.8	86.9

Besides, the accurate forecasts obtained for 2009 and 2010 with Model 1 are showing that the big concern is to forecast accurately the confidence index. In that context, it is interesting to note that IHS/Global Insight has stopped producing consumer confidence forecasts.

The CSI forecast values are much higher than what has been really recorded and it explains in great part the lack of forecast accuracy obtained for the out-of-sample data from 2008 to 2010.

5.6.6. Maturity impact on the models´ results for the supply side

Although the confidence indices seem to have no explanatory power by itself, regarding air travel demand forecast, in the absence of macroeconomic variables, they seem helpful in improving forecast values during the last 10 years when periods of uncertainty are covered for both the Legacy and the Low Cost carriers.

However, the results are more significant for the traffic carried by the Legacy carriers compared to the one carried by the LCC segment.

This result could suggest that the forecasting power of the confidence index is linked to the maturity of the demand on each segment of the US Domestic market. Indeed the econometric models for air travel demand (before introducing the confidence index) are only including the ´´income´´ driver as explanatory variable for the Legacy carriers, while for the LCCs, the model is including in addition the ´´price´´ effect, through the yield.

Based on the definition seen in the previous chapter on maturity, air travel demand for the legacy carriers on the US Domestic market has reached the ‘Full' maturity stage as the income elasticity is unity (when including the confidence index) or below (before including the confidence index). This is not the case for the air travel demand linked to the LCC segment where the income elasticity in the model is around 2.5.

In addition, in the past, a significant part of growth allocation was attributed to network development and as per today the hub networks of the legacy carriers have no great possibility to expand due notably to capacity constraints in major airports.

In the coming years, the routes that passengers actually fly will depend not only on the route they want to take, but also on what the airlines can profitably offer in a challenging market environment (Airbus, 2009). Therefore the network expansion can only be accommodated by LCCs through the opening of new point to point routes outside any hub network. Besides, at the opposite of the legacy market which is driven by organic growth (income and wealth), the LCC market is driven by price.

Some authors are questioning the fact that the GDP elasticity is not the best measure for income elasticity of air travel demand, as at the opposite of the disposable income, GDP is an aggregate measure which includes both income changes but also population changes.

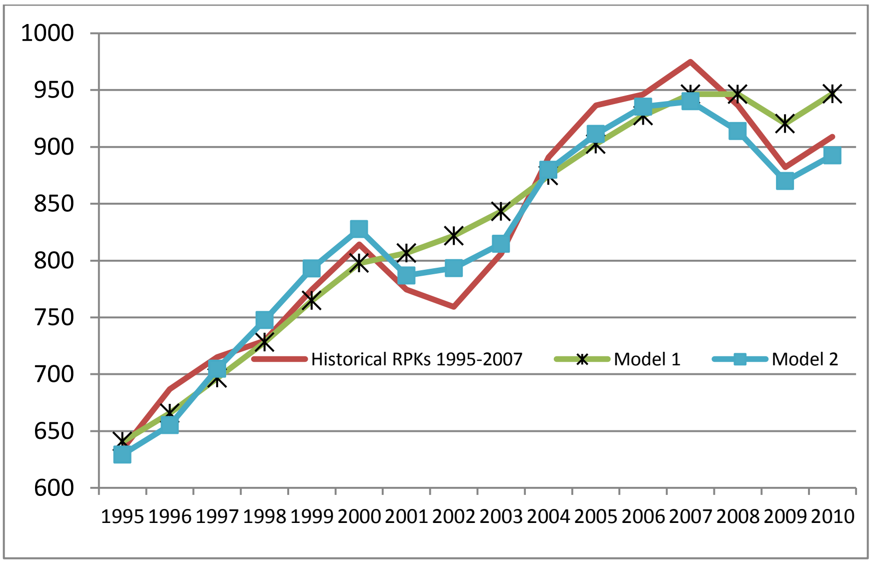
For instance, Graham (2006) found that consumer expenditure is arguably a better measure of personal income than GDP. In a CAA study (2005), the level of the consumer expenditure is seen as the main long-term driver of air travel demand for a specific market and it is often used to indicate its maturity level. As shown for instance by Carroll et al (1994), measures of consumer confidence are highly correlated with real consumption. In the United States, the correlation between the CSI and consumer expenditure has been computed at 0.28. The significance of the consumer confidence index (when associated to GDP) in the model for the legacy carriers is confirming the maturity of the demand linked to that segment (through its correlation with consumer expenditure), as it adjusts the income elasticity around 1.

5.6.7. The global US Domestic traffic in the 1995-2007 time span

Finally, when modelling the global US Domestic traffic from 1995 to 2007 following the same process described before, the best first model (model 1) found is based only on Real GDP, and the second one shows CSI current significant enough to appear in the model at a second stage (model 2). Model 2 improved significantly the Adjusted R-Squared and the t-value of the variable RGDP 95-07, while decreasing the RMSE. The detailed results of the stepwise regression for both models are shown in Appendix S.

As shown in Figure 32, the variable CSI Current improves significantly the goodness of the fit in 2001, 2002, 2003, 2008, 2009 and 2010.

Figure 32: Goodness of the fit between Model 1 and 2 for global RPKs 95-2010

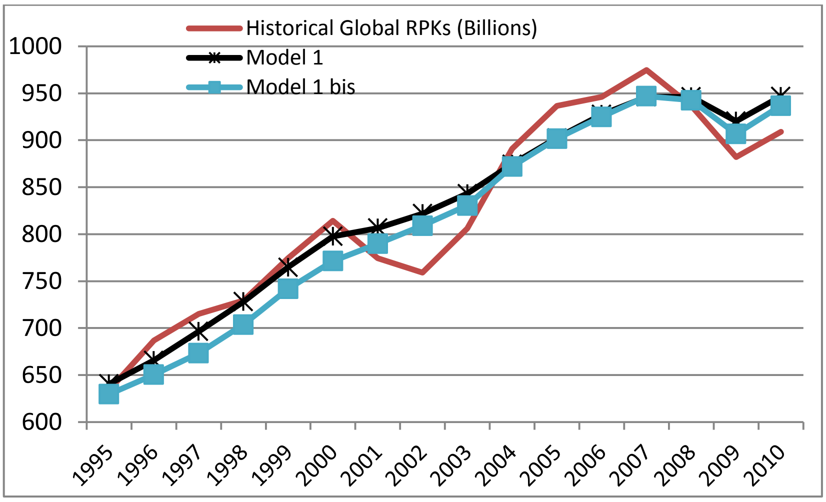


More generally speaking, between 2000 and 2010, Model 2 is performing better than Model 1, as the moves in confidence index are able to reproduce the various peak and troughs of traffic movements during the last ten years.

The final step consists in linking all these results in order to establish the method that gives the best forecast accuracy for the global Domestic US traffic.

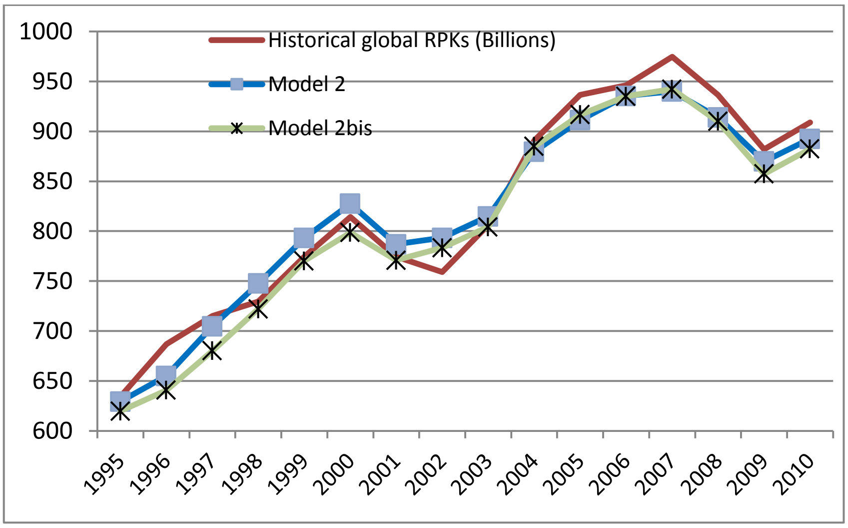
When comparing the sum (Model 1 Bis) of the Models 1 built for Legacy and LCC segments to the Model 1 of the global traffic, it shows a clear improvement during periods of slowdown in traffic growth like in 2001, 2002, 2003 and 2009.

Figure 33: Goodness of the fit between Models 1 and 1 bis for the global RPKs



Then, it is necessary to perform the same exercise with all the models 2 including the CSI Current (Model 2 bis is the sum of Models 2 established for Legacy and LCCs) and that have already been identified as performing all better than any of the models without CSI.

Figure 34; Goodness of the fit between Model 2 and 2 bis for the global RPKs



In this context, the 2 models are performing similarly both in normal periods than in periods of high growth or in periods of crisis. The inclusion of the CSI Current in all the forecasting equations has enabled to reconcile the Top Down with the Bottom-Up approach, especially in the last decade.

Table 19: Comparison of forecast errors for Models 1, 1 bis, 2 and 2 bis

Year	Historical global RPKs	Model 1	Model 1 Forecast Error	Model 1 bis	Model 1bis Forecast Error	Model 2	Model 2 Forecast Error	Model 2bis	Model 2bis Forecast Error
1995	634	641	**1%**	630	**1%**	629	**1%**	620	**2%**
1996	687	666	**3%**	651	**5%**	655	**5%**	641	**7%**
1997	715	697	**3%**	673	**6%**	705	**1%**	680	**5%**
1998	729	728	**0%**	704	**4%**	748	**2%**	722	**1%**
1999	775	765	**1%**	742	**4%**	793	**2%**	770	**1%**
2000	814	798	**2%**	772	**5%**	828	**2%**	799	**2%**
2001	775	807	**4%**	790	**2%**	787	**2%**	771	**0%**
2002	759	822	**8%**	809	**7%**	793	**4%**	783	**3%**
2003	806	843	**5%**	831	**3%**	815	**1%**	804	**0%**
2004	891	875	**2%**	872	**2%**	880	**1%**	885	**1%**
2005	937	902	**4%**	902	**4%**	911	**3%**	917	**2%**
2006	946	927	**2%**	925	**2%**	935	**1%**	935	**1%**
2007	975	946	**3%**	947	**3%**	940	**4%**	942	**3%**
2008	937	946	**1%**	943	**1%**	914	**2%**	910	**3%**
2009	882	920	**4%**	907	**3%**	870	**1%**	857	**3%**
2010	909	947	**4%**	937	**3%**	892	**2%**	882	**3%**

At this point, it is important to compare the average annual traffic growths registered with the ones established by Model 1 bis and Model 2 bis, based on both a segment approach and the inclusion of confidence index for Model 2 bis. This will enable to test the forecasting accuracy for the medium and the long term.

Table 20: Comparison of current and modelled traffic growth

AAGR	**Historical traffic**	**Model 1 bis without CSI Current**	**Model 2 bis with CSI Current**
2000-2010	1.1%	2.0%	1.0%
1995-2000	5.1%	4.1%	5.2%

The model 2 bis built on a bottom-up approach including confidence index as explanatory variable is showing the greatest forecast accuracy on both a medium-term period, 5 years and a longer term period, namely 10 years.

5.7. Conclusions

In this first case study, we have used existing methods to investigate whether or not indexes of consumer confidence are helpful in improving forecasts of air travel demand. The results obtained for the Domestic US air travel market showed that the consumer confidence index has some ability to improve the forecasting accuracy of the forecasting models.

In parallel to this global approach, a more in depth analysis was conducted on the demand forecast linked to the different segments of the supply side, namely Legacy (including Regional) and Low Cost carriers for the US market. Through that further study, consumer confidence appeared as a statistically important determinant of air travel demand, especially for Legacy

carriers, in periods of elevated uncertainty, as it was the case in the 1991-1992 crisis or in the aftermath of the 2001 attack, as well as in 2008 and 2009.
The addition of the CSI current index increases the goodness of the fit, however, none of the confidence indices seem to have an explanatory power by itself, regarding air travel demand forecast, in the absence of macroeconomic variables. Though consumer confidence indexes in some specifications are significant in sample using latest-available data, as well as for some of the out-of-sample data, there is no clear evidence that the use of such indexes improves short-term traffic forecasts significantly, as it appears that the main issue is linked to the quality of the forecasts of the consumer confidence indices.

According to the results obtained for this first case study, confidence appears to be useful to improve forecast values during the last 10 years, and confidence indices appear to be more helpful when periods of uncertainty are covered. In the stepwise process, the value of the CSI Current has always been chosen in priority to be included in the forecasting equation, preferably to the CSI expected value or to the total values of the CCI and the CSI. This is indicating that the actual mood of the consumers is playing a bigger role in their air travel spending decisions, at least when referring to the cultural and psychological side of the characteristics of the American passenger.

Besides, the results found for the Legacy and the Low Cost segments are suggesting that the forecasting power of the confidence index could be linked to the maturity of the demand on each segment of the market. However the differences between Legacy and Low Cost carriers are fading away, and as the US's traditional legacy carriers have lowered their unit costs by an estimated of 20% from 2001 to 2010, they are more and more able to match the low fares applied by the LCCs. This happens mainly because the legacy carriers appropriated some elements of their low-cost rivals' business design (Taneja, 2003), by increasing their online sales, reducing their commissions to travel agents, and improving the productivity of their resources.

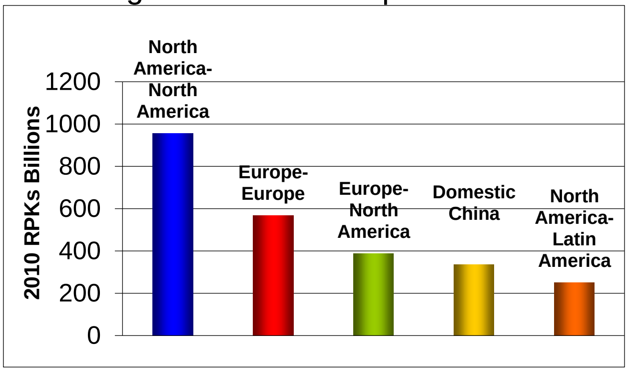
In parallel, the ability to stimulate new demand while complementing other types of airlines is what makes LCC strong, but most low-cost carriers have not matched the level of progress in efficiency reached by some legacy carriers. In fact, some of their costs have actually risen over the past few years, as they are extending their network range and adding some frills. For these reasons, the forecast for each segment will tend to be rather the same in the next decade.

As a next step, it is necessary to check these results for other markets, choosing the major markets, but also the ones where consumer confidence measures are available, as it is the case for USA, EU, China, Japan, Mexico, Australia and Thailand, showing however various data range availability according to the countries.

Taking into account the data available for the top five markets, the next study case chosen is the European market, including both domestic traffic within each country and traffic between each European country.

Therefore the second case study described in the next chapter is appraising the forecasting performance of the consumer confidence index value when applied to the European air travel market.

Figure 35: World Top five traffic flows



Source: ICAO

However, to keep homogeneous results, in order to be able to draw more general conclusions it will be necessary to be consistent with the data set used (traffic or economic variables), as well as with the forecasting horizon and the evolution of the relationship between the variables, while keeping in mind that the years of traffic slowdown may not be the same for all the markets. Moreover, a closer look to the definition of consumer confidence according to each country has to be set, in order to enable the comparison of the forecasts results.

6. SECOND CASE STUDY: THE EUROPEAN AIR TRAVEL MARKET

The major question raised by trying to test the consumer confidence in two different markets is the comparability of the nature of these markets as well as the consistency of both consumer confidence measurements.

The first factor to take into account is the nature of the market, as in non-liberalized markets, there is no significant segmentation. As the first case study was the US Domestic market which is a liberalized one, the geographical definition of the European air travel market, for this study, has to correspond to a liberalized market definition. The limits of the European Union single sky are defining the initial scope of the European air travel market to be considered.

For comparison purposes, the option of considering only the domestic European market was not retained as the EU domestic market is less than one third of the US one. The aim is to compare markets with similar size, and as the EU single sky, is associated with the free movement of people within the different EU countries, the traffic to be considered was enlarged to the Domestic one associated with the Intra-EU countries one.

There are some important structural differences in the air transport market in the EU and the USA, as for instance in Europe average distances between cities are shorter and competition from alternative transport modes, notably road and railways, is much stronger than in the US. Europe has a far higher number of airlines, while conversely European carriers' average size is much smaller, both in terms of number of aircraft operated and market shares.

6.1. The market context

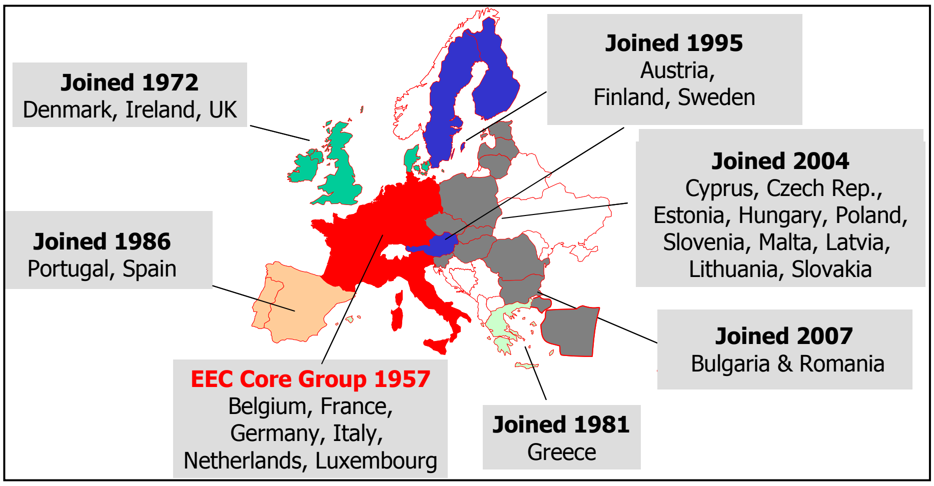
As Europe is a blend of smaller developing economies and larger mature ones, the Commission's approach for creating a single market in European air travel, initially launched in 1987, was deliberately phased in three stages to avoid the market disruption that was witnessed in the US approach to liberalisation.

The first package, community licence was implemented in 1987 while the second one, freedom of access to the market was set up in 1990. The third progressive one which occurred between 1993 and 1997 has gradually introduced freedom to provide services within the European Union and leading in April 1997 to the freedom to provide cabotage[35]. As part of freedom of access to the Community market, freedom with regard to fares was an essential part of the whole liberalisation process.

The constant evolution of the number of countries in the EU (on-going process), as shown in the Figure 36, as well as the existence of a restricted Eurozone inside the EU, is increasing the issue of the initial market definition.

[35] Cabotage: the right for an airline of one Member State to operate a route within another Member State

Figure 36: European Union countries



Source: EU commission

The final element to consider before freezing the definition of the European air travel market is to check the consumer confidence availability in the different EU countries.

6.2 The EU Consumer Confidence Index definition

Although the Michigan survey has been the model for other surveys worldwide, each national institute has adapted the set of questions to national peculiarities, thus providing different measures of sentiment.

However, the consumer confidence indicator which is published by the European Commission for all EU countries is built on harmonized monthly surveys with identical questionnaires in all countries. The surveys are conducted on behalf of the European Commission by various national institutes during the first ten working days of the month, and the results are published in the first half of the following month and are seasonally adjusted.

6.2.1 Construction of the EU consumer confidence index (EU CCI)

The data are drawn from the Business Surveys Unit of the European Commission, and in order to achieve representativeness, the bigger member countries use a larger sample. Participants in the survey are usually selected by a simple random sampling. The most widespread method is the telephone interview and monthly telephone surveys of about 2000 households are conducted by each national statistical institute, as for instance, INSEE, GFK and ISAE for France, Germany and Italy respectively.

The consumer confidence indicator is based on the computation of the answers to the questions from the consumer survey which consists of 12 questions (shown in Appendix T). Consumers are questioned about their opinion of the general economic situation and their financial situation both in the previous and the next twelve months, and whether it is a good time to make major purchases now. These questions show that this indicator contains two elements. The questions concerning the general economic climate measure the ‘feel good factor’ of consumers, while the other questions go into factors that influence the demand for goods by consumers such as their purchasing power and their willingness to buy.

The consumer confidence indicator for each EU country is the arithmetic average of the balances (in percentage points), seasonally adjusted, of the answers to the questions on the financial situation of households, the general economic situation, unemployment expectations (with inverted sign) and savings, all over the next 12 months.

In order to compute EU aggregate results for the consumer survey, specific weights are given to the Member States. These weights are revised on an annual basis, and as shown in Appendix U from 1985 to 2009, reflect the contribution of the Member States in the EU private final consumption expenditure. A two-year moving average weight based on private final consumption expenditure at constant prices is used

Behind this mathematical construction of the CCI, the differences noted in each country´s indicator (through the questionnaire´s answers) are also related to specific factors, such as historical developments still present in the collective unconscious. The behavior of the households of a country as a whole is assumed to present some specific features, probably related to particular events occurred far in the past (e.g. the hyperinflation in Germany) or in more recent times (e.g. the sharp deterioration of public finances in Italy or the debt crisis in Greece).

The relationship between consumer sentiment and macroeconomic variables may also reflect the characteristics of the economic environment, such as the degree of competition of the markets, the flexibility of the economy (especially the labor market), the nature of the welfare state and the strength of political institutions. Acemoglu et al (2002) showed that households´ attitude may be influenced by the presence of strong economic and political institutions, as institutions can be considered as a major determinant of economic performance.

As described, in the previous case study, the US Consumer Sentiment Index has two components, the Current and the Expected one, and two of the five questions of the survey ask respondents to assess present economic conditions. However, although in the EU survey, there are also Ex post questions and Ex ante questions, similar to the assessments made in the US survey, there are no two different component indexes in the EU confidence indicator.

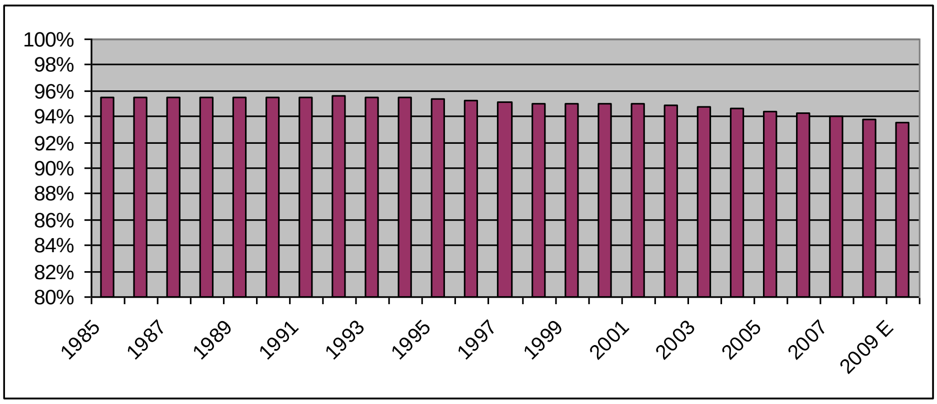
The comparative answers to the survey for some of the EU 15 States, tabled in Appendix V, show both predictable (e.g. people know the past better than the future) and surprising (e.g. people tend to judge over-pessimistically and to forecast overoptimistically) perceptions about the economic situation. At the opposite of the US confidence results, the current situation is seen as worse than the expected one. Clearly, the cultural dimension of the confidence index is appearing behind the technical design of the CCI quantification scheme.

6.2.2 Data availability and time span definition

The different starting dates for each survey are detailed in Appendix W, and January 1985 is the one for nine out of the 27 EU countries. On the initial fifteen EU members, exemptions are Austria (starting date 1995:10), Finland (1987:11), Luxembourg (2002:01), Portugal (1986:06), Spain (1986:06), and Sweden (1995:10). For the countries that have joined the EU later, like Estonia, Czech Republic, Hungary, Slovenia, Slovak Republic, the surveys started after 1992 or 1996, while for Romania, Cyprus, Latvia, Lithuania, Poland and Bulgaria, the survey started in 2001. It is noteworthy that Malta has no confidence survey implemented. Therefore the EU 15 basis seems to produce the most consistent data sample.

In order to be consistent with the time period used in the first case study and to be able to evaluate the forecasting power of the confidence index during crisis times it is imperative to consider the years 1991 and 1992, and to start the modeling some years before this period.

Figure 37: Evolution of the percentage of the EU 15 consumption over the EU 27 consumption



Source: Eurostat

Besides, it is still necessary to assess the EU 15 country weight on the whole EU 27 market as it is the basis for the confidence index calculation. As shown in figure 37, the percentage of the EU 15 consumption on the consumption of the whole EU 27 has not varied much since 1985 and is still representing more than 90% in 2010.

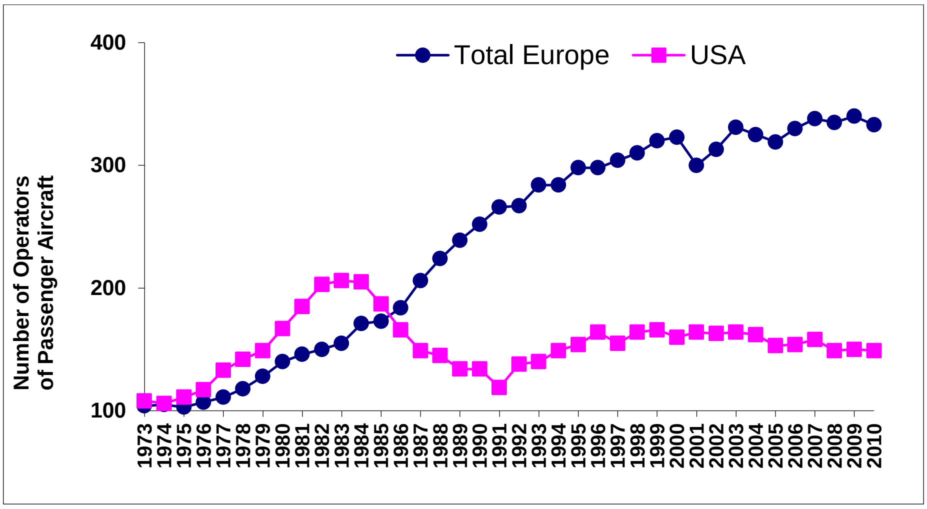
In light of the above, it has been decided that the EU definition to be used for this study will be restricted to the EU 15, while the corresponding weight of the air travel supply side limited to the EU 15 compared to the EU 27 basis must also be assessed.

6.3. The supply side segmentation

The opening up of a market previously protected from competition usually results in a first phase in which the number of participants in the industry increases. This is followed by a second phase of consolidation whereby the number of firms decreases and their size increases. Air transport seems to have followed this process in the USA. Europe, which undertook liberalization some ten years later, still seems to be in the first phase, as shown in Figure 38. This status is in great part due to the progressive geographical extension of the EU countries definition.

In 1997, 304 European airlines were performing commercial operations, while in 2010, this number reached 333, taking into account failures and mergers.This increase in the number of airlines has allowed the emergence and fast development of a new type of airline in Europe Consequently the number of air routes between different Member States of the European Union has increased by some 30% since 1993.

Figure 38: Evolution of the number of operators in Europe and in the US, before and after deregulation implementation



Source: OAG

For this second case study, traffic data are provided by various data sources including, ICAO, IATA, OAG, Association of European Airlines (AEA), European Regional Airlines Association (ERAA) the airlines annual reports and Ecole Nationale de l´Aviation Civile (ENAC) which gathers city-pairs data from each national aviation authorities.

Table 21: Comparative annual traffic growth between 2000 and 2010

YEAR	Total EU traffic	Network traffic	Charter traffic	LCC traffic
2000	341	165	140	36
2001	347	167	138	43
2002	345	166	126	53
2003	371	169	130	73
2004	411	180	137	94
2005	462	202	142	118
2006	488	210	145	133
2007	531	223	150	158
2008	557	222	147	188
2009	535	210	127	198
2010	582	230	135	216
AAGR 2000-2010	**5%**	**3%**	**0%**	**20%**

To avoid difficulties arising from differences between the data sources, only one source is used on any particular traffic sub-market. In a very few cases where no data are otherwise available for a particular traffic flow, estimation of actual traffic has been extracted from OAG in terms of ASKs, corrected with assumptions about average load factors.

Besides, as shown in Table 21, the passenger traffic growths registered in the last ten years by the different European supply side segments are significantly different. Hence, the consumption pattern of the passenger travelling on each segment is probably different and the Consumer Confidence Index associated to the fare effect may play a different role on the modelling of each segment.

6.3.1. The LCC segment

This new airline business model, for which a liberalised market is a necessary framework was imported from the US and adapted later in Europe after the implementation of the deregulation. The emergence and the growth of the LCCs have had a significant impact on airline competition, airline business models and air travel in general. However in Europe, there are several business models for LCCs. Therefore based on the definition provided by ICAO, the list of the European LCCs taken into consideration for this study is in Appendix X, restricted however to the airlines having their principal place of business in the States members of the EU 15.

6.3.2. The Charter airline segment

Before liberalisation in the European air travel market, the European airline industry was clearly divided into three types of carriers: national carriers, regional carriers and charters.

Therefore the EU air travel market segmentation is more complex than in the US, as there is an additional segment, the Charter one. The rise of the low cost airlines has led to the practice of splitting the industry into what are called “Network”, “Charter”, “Low Cost” and “Regional” airlines with membership in each group determined by the operating nature of the carrier. The most important issue was to establish a list of the airlines categorized in each supply side segment

Charter airlines are truly low-cost carriers, with an even lower basis in their operating costs, as shown by Beck and Williams (2003). Besides, according to the evolution of the leisure traveller behaviour, charter airlines increasingly sell airline seats independent of broader holiday packages. Most charter carriers are developing into hybrids, combining charter business with these new retail operations. The best example is Air Berlin, whose overall sales are split evenly between the low-cost-carrier and charter models, and has rebranded itself in 2003 as a Low Cost Carrier.

This matter of fact is making difficult the definition of a clear segmentation as well as the identification of the airlines to be included in each supply segment.

In order to differentiate LCCs from charters airlines, the distribution channel was taken as the major criterion, namely:

a) Direct through internet reservations for LCCs
b) Via Tour Operator reservations for integrated or independent charters

Unfortunately statistic data concerning charter airlines are scarce and poorly detailed. However it is estimated (Civil Aviation Authority CAP 685 –The single European Aviation Market) that in 1996 the European charter airlines carried 77 million passengers, which compares with the estimated scheduled total of around 240 million. In terms of RPK the charter share is higher, since on average the passenger distance is longer for charter service than for scheduled service. It is estimated that in 1998, the charter industry share in Europe was about 50% of the total European air travel market. The same issue of blurring frontiers as the ones between the charter airlines and the LCCs is also occurring with the network carriers as some previously categorized as charter airlines like Spanair, are now reported as network carriers.

6.3.3. The network and the regional segments

The largest European airlines are similar in size to the largest American ones but a typical characteristic of the European airline industry is the existence of a second layer of relatively small airlines with a global vocation.

In terms of operating pattern, the hub-and-spoke pattern is characteristic of the network airline business model, as well as the regional airline one. In hub-and-spoke operations, traffic is concentrated into a single, centrally located destination (the hub) which is used as a connecting point for passengers traveling between any other pair of destinations in the network.

The evolution of the network carriers within the EU is well defined by the community airlines belonging to AEA grouping mainly network carriers, while ERAA is representative of the regional airlines operating in Europe.

Hub and spoke and low cost are the main emerging tendencies of the last ten years, but they are not mutually exclusive, and some airlines follow patterns that are a combination of the two. In the long-term, it would become more and more difficult to make a sharp distinction between LCCs and other airlines based on the services they offer and/or business models. This is because major network airlines have been shifting their focus towards achieving cost reductions and changing the way they operate in response to growing cost and competitive pressures from LCCs. Increasing convergence of services and business models might not make the LCC tag relevant at some point in the future. Since LCCs could put away or modify their business models, network airlines could also transform themselves into LCCs, as it is the case for Aer Lingus which used to be an AEA airline before rebranding itself as an LCC in 2002.

In addition, an important work of data cleaning was necessary as some AEA airlines, notably Air France and Lufthansa are reporting their traffic data by including the regional airlines affiliated to them or operating under their call sign. The list of AEA and ERAA airlines in Appendix Y is clearly showing this risk of double counting for airlines like Brit Air or Eurowings.

More generally speaking, there is a tight link between the network carriers and the regional ones, as a great majority of regional airlines are privileged partners (code-sharing, franchisees, etc..), making it difficult to separate the origin of the traffic. Therefore, when talking about traffic of network carriers, it will include traffic of the regional airlines.

Finally, according to the scope of this study, only the airlines having their principal place of business in the States members of the EU 15 need to be taken into account. Therefore it was necessary to take out from the AEA reported traffic for domestic and intra-Europe, the traffic of Turkish airlines or Tarom, for instance.

The ideal cleaning would have been to take out from each carrier´s reported traffic, the traffic registered between city-pairs not part of the EU 15 geographical definition, but this was impossible to achieve as no reliable data are available, except the OFOD and the TFS published by ICAO, but still not achieving a complete geographical coverage.

6.3.4. Issues linked to the segmentation

The new segment represented by the Low Cost Carriers has grown extremely fast after the completion of the third package in 1997. The resulting fares drop leaded to the creation of new markets and traffic growing to three folds previous levels on some routes.

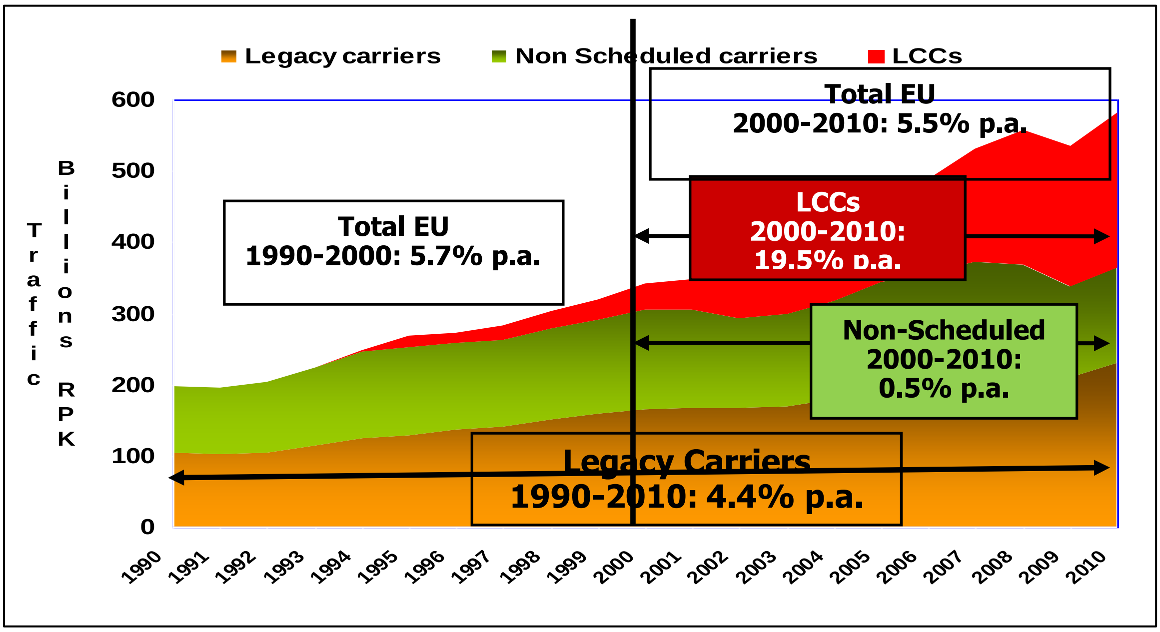
In 2000, the LCCs' market share was only 11% of the total EU air travel market, and ten years later, this market share has more than doubled. Some of the LCC market share has been taken from the traditional network carriers, another one from the charter airlines, and another portion is coming from people, who would not fly if it were not that cheap.

As shown in Figure 39, the traffic growth is quite different for passengers carried by LCCs and for those flying on charter and network carriers or regional carriers operating for the network carriers. Therefore, it is confirming the need to detail the air travel demand according to the supply segmentation.

However, as already mentioned for the US Domestic market, air travel market segmentation through the supply side in the future, will become less and less obvious, as frontiers are blurring out between network carriers, Low Cost Carriers and Charter airlines.

Taking into account the low ratio of net margin on revenues and the volatility of oil prices, all airlines are poised to reduce their costs, while the expansion of LCC numbers leading to more competition on this segment, is pushing LCCs to introduce more frills, as price cannot be anymore the only differentiator.

Figure 39: Evolution of Total European air travel market between 1990 and 2010 by supply side segments



Source: ICAO, ENAC and AEA

For the evaluation of the Confidence index, major trends in the traffic growth must be analysed to highlight key dynamics that govern the European air travel demand, as the European air transport industry has evolved through periods of deregulation, economic growth, the financial and economic crisis of 2008 and 2009, and lately the Euro crisis prompted by the debt of some European States.

6.4. Air travel demand levers in Europe

The analysis of the traffic pattern between the successive 10-year periods, since the eighties, has shown obviously different growth rates due to events that have favoured traffic increase, while others have slowed down it. The different oil crisis, the Gulf wars, the WTC attack and lately high oil prices combined with the financial crisis are among the forces that have constrained the European air travel demand.

The major forces that are driving airline traffic and enabling to assess whether the patterns of a specific market has changed is linked above all to its regulatory status. Indeed, the liberalisation of the US and the Europe's civil aviation markets aimed at fostering competition among airlines by removing regulatory constraints on both airlines' routes and pricing. Passengers were expected to benefit from lower fares, higher flight frequency and more routes, leading to a change in air traveller's behaviours with a significant impact on air travel demand modelling.

While business travel in Europe represents about 45% of travel by air, tourism and VFR accounts respectively for 40% and 15%.

The air travel demand linked to business travel is representing approximately the same level in Europe than in the US. However, in the US, there is a higher proportion of VFR travel (35%) as the population is more mobile than in Europe, as for instance, one in five Americans changes address every year.

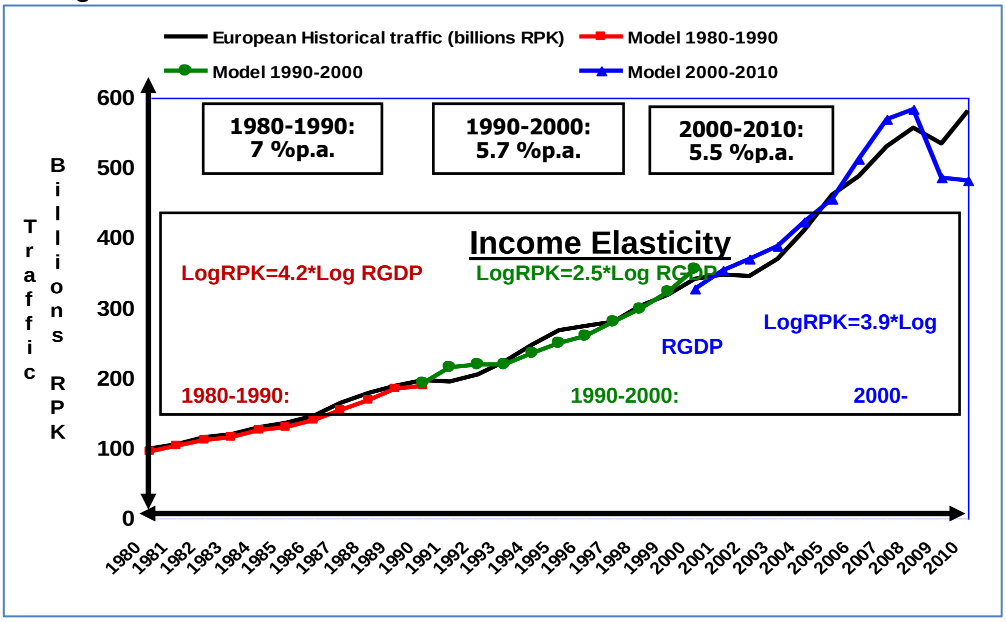
The importance of the tourism demand in Europe is reflected through the consequent weight of the non-scheduled traffic in the EU, which is totally marginal in the US.

Another key issue is to estimate the degree of maturity of this market, as a whole but also by supply side segment. Prior to liberalization European leisure travelers relied on charter services by integrated tour operators for access to tourism destinations in Europe. In 1987, up to 40% of all air passengers within geographical Europe were carried by charter airlines (Barrett, 2004). Most likely, these charter services were not all included in the ICAO dataset because ICAO reports both scheduled and non-scheduled passengers without specifying if they are carried by a non-scheduled airline. Following liberalization, the charter services were replaced in some regions with scheduled services operated either by network carriers or LCCs. As a result, these services may now be reported in the ICAO dataset, reflecting that part of the growth in air passenger traffic in Europe can be attributed to the fact that prior to the nineties, the ICAO data was under-representing the total passenger traffic in Europe.

6.4.1 Level of market maturity and fares trends

Modeling the traffic between three successive 10-year periods, since 1980, has shown dramatic changes in the elasticity to income, as shown in the figure below, leading to re-examine empirical modelling of air transport demand in the EU 15 air travel market.

Figure 40: Evolution of the income elasticities from 1980 to 2010



Source: ICAO and IHS/Global Insight

The EU liberalization prompted the emergence of a multitude of new airlines together with a fundamental restructuring of existing full-service airlines that have stimulated the traffic growth, especially in the last decade, confirming therefore that the EU air travel market is still not a mature one.

As shown in Figure 40, when modelling traffic in global in the European market, it appears obviously as a non-mature market: the income elasticity is increasing from 2.5 in the 90-2000 decade to 3.9 in the 2000-2010 decade.

Then going through the supply side demand modelling it appears in equation (18) that the income elasticity for the traffic carried by the network carriers is estimated at 0.9 between 1995 and 2010 which is representing a very mature market in the legacy segment, while the price elasticity is more typical of a business demand.

European Network carriers:

LnRPK= -2 + 0.9 LnRGDP/Cap – 0.6 LnReal AEA yields (18)

Table 22: Model specifications for Network carriers

Variable: Log RPKNetwork	Parameter Estimate	Standard Error	Type II SS	F Value	Pr > F
Intercept	-2.00079	3.36929	0.00050930	0.35	0.5628
LnRealGDP	0.93732	0.30994	0.01321	9.15	0.0098
LNReal Yields AEA	-0.61592	0.17899	0.01710	11.84	0.0044

In the Low Cost Carriers segment the income elasticity shown in equation (19) is significantly above the one of the 2000-2010 decade for the global European traffic at 12.2: it is clearly a non-mature segment, giving an explanation of the high income elasticity found in the last decade for the global European air travel market.

European LCCs::

*LnRPK= - 122.5 + **12.2** LnRGDP/Cap* (19)

Table 23: Model specifications for LCCs

Variable: Log RPK LCCs	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-122.50339	12.30902	-9.95	<.0001
LNReal GDP Per Capita	1	12.21413	1.18745	10.29	<.0001

Regarding the results for the Charters as represented in equation (20), the low income elasticity combined with the stagnant traffic growth registered in the last decade are confirming the maturity of this segment.

European Charters::

LnRPK= - 2.4 + ***0.7*** *LnRGDP/Cap* (20)

Table 24: Model specifications for Charters

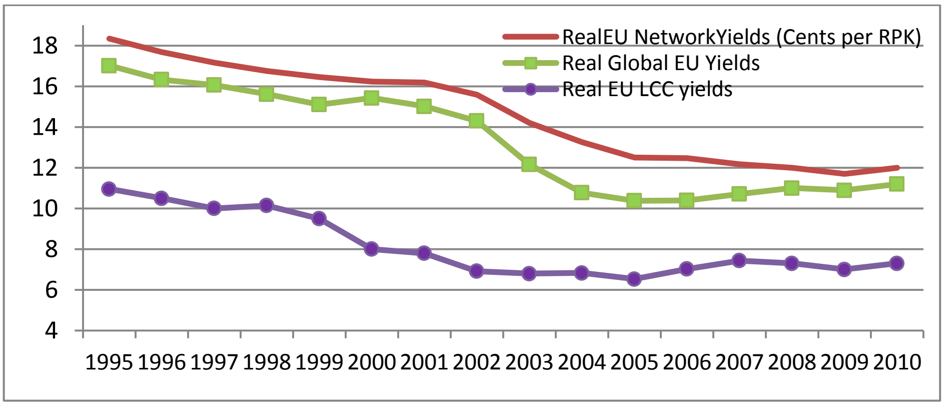
Variable: Log RPKCharters	Parameter Estimate	Standard Error	Type II SS	F Value	Pr > F
Intercept	-2.41719	1.53937	0.00438	2.47	0.1387
LNReal GDP Per Capita95	0.70569	0.14850	0.04008	22.58	0.0003

In terms of market typology, the results for the European air travel market are confirming the ones found for the Domestic US air travel market, namely that the traditional demand segmentation business vs leisure is becoming less significant than the supply segmentation, network carriers vs Low Cost Carriers and non-scheduled carriers in the European air travel market.

6.4.2 Yield trends

After the removal of the restrictions posted on airline industry in a regulated mode, airfares have taken a more and more complex structure, and traditional bond between airfares and distance has broken down. When comparing in the Figure 6, the yield evolution on the European air travel market between 1995 and 2010, LCC[36] yields decreased by an annual 2.7% (from a lower basis), while AEA real yields decreased by 2.8% per year, leading to a global annual decrease of 2.8%.

Figure 41: Comparison of real yield decrease between EU network and LCCs



Source: AEA and ICAO

[36] Ryanair yields are taken as a reference for the LCCs yields

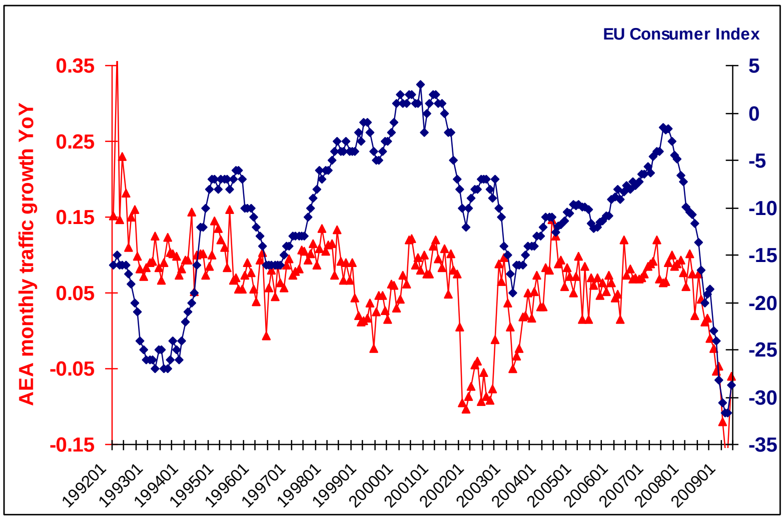
The elasticities associated to the models describing the evolution of the EU air travel market, with established routes and defined fares, are now obsolete, because of the structural change which has enabled free entry and price competition.

In the first case study, the research indicated that airline demand is driven by price reductions rather than income changes and that the share of income spent on air travel is not showing much growth.

6.5. Evolution of air travel demand and consumer confidence

Periods of high economic or political uncertainty are often associated with high volatility of consumer confidence, suggesting that large swings in confidence as shown in Figure 42, are also particularly important for air travel demand, as the corresponding spending are typical discretionary expenditures. In the last ten years, a correlation is noticed between the lagged value of air traffic growth and the CCI value.

Figure 42: Comparative evolution of the EU CCI and the AEA monthly traffic growth in the EU market



Source: AEA and IHS/ Global Insight

In order to cross-check the results found in the first case study, this second case study is attempting to provide a formal evaluation of the EU consumer confidence index as a potential variable to better determine air travel demand in Europe.

However, the results might be deceiving, as among other potential factors expected to impact air travel demand, the case of oil price is a misleading example according to the market considered.

During the last peak in oil price registered in the first half 2008, the dollar's weakness against the euro has helped cushion the European airlines against the high price of oil, traded and billed in dollars.

In addition, to this issue of exchange rate, the fuel surcharges practices as well as the different instruments used to hedge the fuel price increases are adding significant burden to the right measurement of the yield, and hence to the quantification of the oil price impact.

6.6. Models, forecasts and results

Similarly than for the first case study it is confirmed that the consumer confidence index cannot establish better forecasts as only explanatory variables introduced in a time series analysis of the European air travel market.

For this test the AEA monthly traffic data have been taken for both the Domestic and the Intra-European market from January 1981 to December 2010.

However, when modelling the traffic with the GDP as first regressor, it appeared significant enough to be included as a second regressor, while improving the forecast accuracy of the model.

The aim is to determine if short-term forecasts in crisis time can be improved by including Consumer Confidence, before reverting to the long-term trend established before crisis.

6.6.1. The data series

After the third package, there are strong reasons to believe that the relationship between traffic, airfares and income has not been the same after and before 1997. Moreover, the number of operators is only starting to stabilize in the last decade. Ideally the data series to study would have been between 2000 and 2010, but it is representing a too short time span to draw relevant conclusions. However, taking into account that we need to compare the impact of CCI for the US and the EU markets during the same time span, the historical data series considered in this study for the global European traffic are starting from 1985. Besides, the regression analysis of the network carriers, charters and LCC data series will start only in 1995, the year where valuable data for LCCs traffic have started to be available.

6.6.2. The OLS regressions during the 1985-2010 time span

The preliminary step is to test the RPKs series from 1985 to 2010 using currently known regressors values in order to determine if the Consumer Confidence Index has any explanatory power in air traffic growth, especially during crisis times, before applying it for forecasting purposes in real time.

As shown in Table Z1 of Appendix Z, W is positive and close to one which indicates normality, for this Log (RPK) analysis. Besides, the null hypothesis for this test is that the data are normally distributed, and as the p-value is greater than 0.05, then the null hypothesis has not been rejected, which is the case for this model.

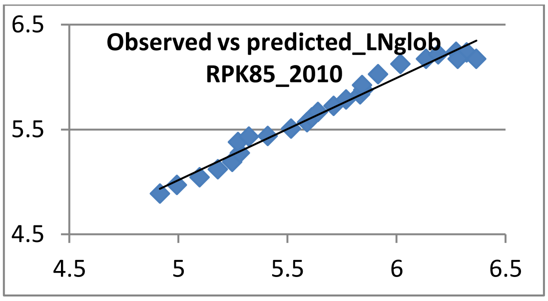
Based on the Log RPKs series going from 1985 to 2010 the following potential regressors are introduced in the stepwise regression: RGDP/Cap, RGDP, RU and Real yields.

The best initial model found, Model 1, is based on Real GDP and Real Yields, as shown in the table Z2 of Appendix Z.

It is understood that for any of the OLS that will be run in this second case study these assumptions will be systematically checked, but not shown in the main text.

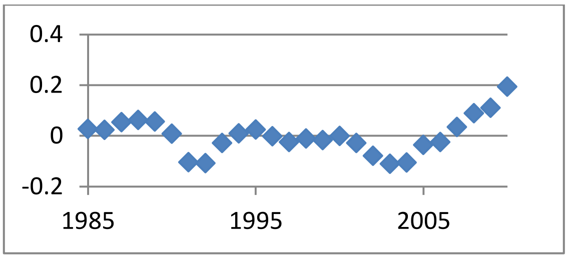
The linearity of the relationship between Log RPK and the 2 regressors is shown in the figure here below

Figure 43: Linearity tests for Log RPK 85-2010



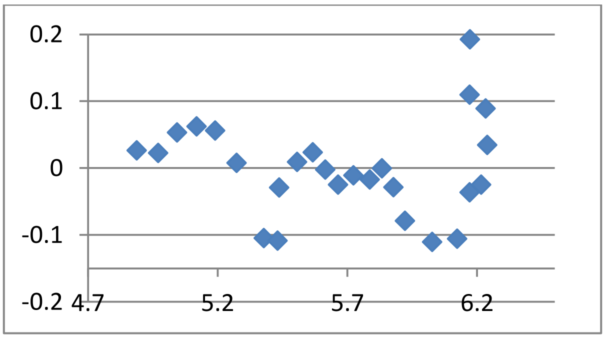
When looking at the autocorrelation plot of the residuals, and based on the sample size, all the residual autocorrelations are between - 0.4 and +0.4, which confirms that the errors are independent.

Figure 44: Autocorrelation plot for Log RPK 85-2010



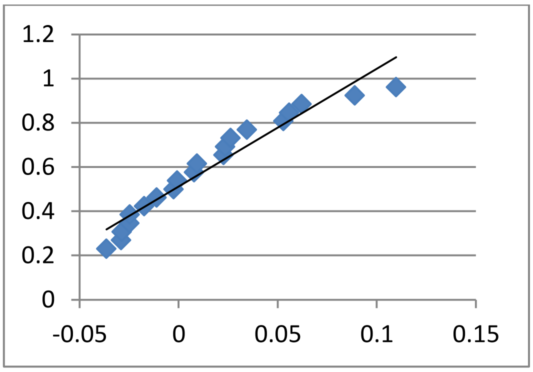
As shown in the graphs above and below, the plots of residuals versus time and residuals versus predicted value of Log RPK are showing no evidence of residuals that are getting larger either as a function of time or as a function of the predicted value of Log RPK.

Figure 45: Homoscedasticity test for Log RPK 85-2010



As expected from points coming from a normal distribution, the normal probability plot is producing an approximately straight line, showing that residuals are normally distributed with 95% of confidence.

Figure 46: Normal probability scatter plot for Log RPK 85-2010



As expected from points coming from a normal distribution, the normal probability plot is producing an approximately straight line, and this result is confirmed by the Jarque-Bera statistic showing that residuals are normally distributed with 95% of confidence. Finally when looking at Influential points the DFFITS values for this regression (in table 25) is showing no influential point.

Table 25: DFFITS test for influential points for Log RPK 85-2010

Year	DFFITS Log RPK 85_2010
1985	0.17521038
1986	0.14212154
1987	0.30970148
1988	0.30538004
1989	0.27945113
1990	0.03153897
1991	-0.399973
1992	-0.3796284
1993	-0.1120736
1994	0.03259987
1995	0.07414054
1996	-0.0087098
1997	-0.067787
1998	-0.0315012
1999	-0.0575198
2000	-0.0057429
2001	-0.2495229
2002	-0.5610835
2003	-0.4417179
2004	-0.8053163
2005	-0.2781395
2006	-0.1346504
2007	0.17394261
2008	0.54180779
2009	0.53884909
2010	1.16178909

Based on this model and leaving in the stepwise process the same regressors than the ones in Model 1, the CCI is introduced in the stepwise box. The stepwise results are showing that Log CCI is not significant enough to enter the equation. It is noteworthy also that when introducing dummy variables equal to 0 for all the years except for 1991, 2002 and 2009 (years identified as showing a traffic decrease) where the dummy variables were equal to 1, the Dummy is not appearing as significant enough to enter the model.

6.6.3. The OLS regressions during the 1985-2007 time span

Therefore the same exercise is repeated with a Log RPK data series from 1985 to 2007. The new Model 1 specifications are quite similar to the previous ones found for the time span 1985-2010, as shown in Table AB1 of Appendix AB.

Based on this new model 1, and leaving in the stepwise process the same regressors, namely RGDP and RYields, the CCI is introduced in the stepwise box. The Model 2 specifications are detailed in Table AB2 of Appendix AB. For both the variables GDP and CCI, a positive sign is correctly calculated since an increase in income or in consumer confidence are expected to have a positive influence on traffic growth, while similarly, for the variable Yields a negative correlation sign is correctly calculated since a decrease in fares is expected to have a positive influence on air travel demand.

The first conclusions are showing that the adjusted R-Squared has improved in Model 2. A higher value of adjusted R-squared is relevant to assess the forecasting value of the CCI as added variable, because the goodness-of-fit has not improved by increasing the number of independent variables as the value of the adjusted R-squared (by definition) is corrected for degrees of freedom.
In both models the F-test has a satisfactory value determining that the models are statistically reliable, and that the observed R-squared is reliable and is not a spurious result of oddities in the data set.
The RMSE in Model 2 has decreased by 21%, hence indicating a better fit of Model 2. RMSE is the most important criterion for fit if the main purpose of the model is prediction.
The first sets of diagnostic tests are showing that the Model 2 including the confidence index performs better than the Model 1.

However, both in Model 1 and Model 2, VIF is very high for the independent variables, real Yields and Real GDP, and as it is higher than10 it is considered to be of concern in terms of potential collinearity.

Table AC1 of Appendix AC presents the correlation matrix of the variables of the model, as well as the VIF, pointing out that a collinearity problem seems to be occurring between Ryields and RGDP. This multi-collinearity issue will be dealt in the section 6.6.4.

Going further in the compared analysis of the two models, additional tests have been computed, shown in Table AD1 of Appendix AD.

When looking at the Mallow's statistic (C(p)), the Model 2 is performing better as it is giving a smaller value of C(p), also closer to the number of parameters in the model. Finally the SSE has decreased in Model 2, indicating a best fit line.

As highlighted in grey in Table 26, the model 2 is showing the lowest forecasting error in absolute value in 1991, 1992, 2002 and 2003, while is in general the models are performing very similarly in terms of goodness of the fit.

Table 26: Absolute values of the forecast errors of Model 1 and 2

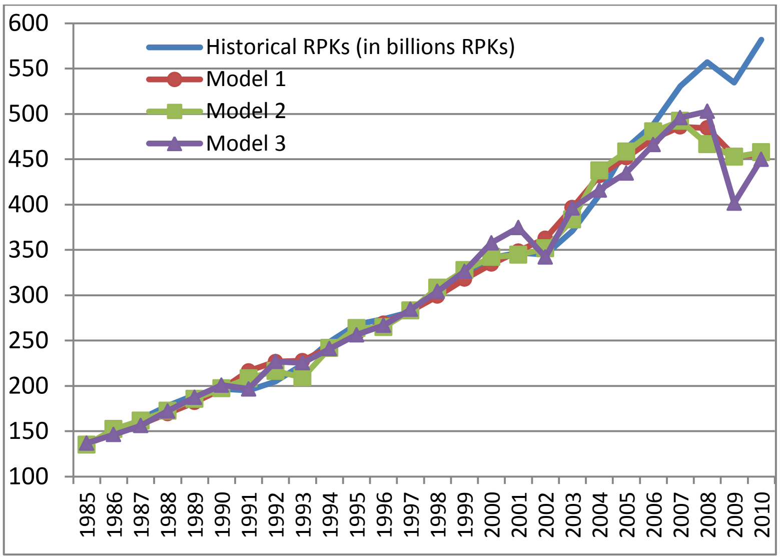
Year	Historical RPKs (in billions RPKs)	Model 1	Forecast Error Model 1	Model 2	Forecast Error Model 2
1985	136	136	**0%**	135	**1%**
1986	147	147	**0%**	152	**3%**
1987	164	157	**4%**	162	**1%**
1988	178	170	**5%**	173	**3%**
1989	190	182	**4%**	186	**2%**
1990	197	196	**0%**	197	**0%**
1991	195	216	**11%**	208	**7%**
1992	205	227	**11%**	216	**6%**
1993	223	228	**2%**	209	**6%**
1994	249	243	**2%**	242	**3%**
1995	268	257	**4%**	264	**2%**
1996	274	269	**2%**	265	**3%**
1997	281	283	**0%**	283	**1%**
1998	303	299	**1%**	308	**2%**
1999	320	318	**1%**	328	**2%**
2000	341	334	**2%**	342	**0%**
2001	347	349	**1%**	345	**1%**
2002	345	363	**5%**	352	**2%**
2003	371	397	**7%**	383	**3%**
2004	411	432	**5%**	437	**7%**
2005	462	452	**2%**	458	**1%**
2006	488	473	**3%**	481	**2%**
2007	531	486	**8%**	492	**7%**
2008	557	485	**13%**	467	**16%**
2009	535	454	**15%**	453	**15%**
2010	582	454	**22%**	458	**21%**

When introducing the dummy variable in the data series 1985-2007 with the RGDP, Real Yields and the CCI as potential variables in the stepwise regression, the Model 3 is showing that only the RGDP and the dummy are significant enough, as displayed in Table AD2 of Appendix AD. In addition the Table AD3 of Appendix AD is showing that the RMSE is still lower in Model 2, while Adjusted R^2 is still higher in Model 2, while C(p) is extremely higher in Model 3 than in Model 2, and in addition AIC, BIC and SSE are still lower in Model 2.

Additional tests should be computed for checking purposes, notably on exogeneity of the regressors as well as on the structural stability of the model.

For the exogeneity test, a t-test was run on the mean of the errors, and according to the value of the t-test related to the number of observations (23), The t-value at $4.3*10^{-22}$ has been found largely below the limit imposed by the number of observations. Therefore, the assumption of strict exogeneity of the residuals cannot be rejected.

Figure 47: Goodness of the fit between Model 1, 2 and 3



However at the opposite of the US Domestic market, the year 2000 cannot be assumed as a break point for the European market, and consequently when conducting the Chow test, it has been found that the model is valid for the whole sample period (cf sub-section 6.6.4).

6.6.4. Comments on multi-collinearity concerns

Traditionally, multi-collinearity has been thought about simply as a problem of having weak data or too little data. For example, Kementa (1971) states "that a high degree of multi-collinearity is simply a feature of the sample that contributes to the unreliability of the estimated coefficients, but has no relevance for the conclusions drawn as a result of this unreliability." Goldberger (1991) states that the problem of multi-collinearity is directly linked to the problem of having a small sample. More specifically, the problem of multi-collinearity is that of having weak data with the result being that each standard error is so large that it is impossible to precisely estimate the related regression coefficients of interest. Thus the problem induced by multi-collinearity is equivalent to the one faced when modelling with a small sample size of data which leads to provide very imprecise estimates of the regression parameters. From this perspective, if the sample size can be increased, then it should be possible to solve the multi-collinearity problem (Kementa, 1971) between the independent variables. This is due to the fact that the confidence interval associated with an estimate is so large that unreasonable estimates are included. From a Bayesian perspective the issue is due to the failure to include sufficient prior information into the analyses about what constitutes realistic estimates for the coefficients (Leamer 1994).

In air travel demand modeling, multi-collinearity pervades time series estimates, as variables such as price and income tend to be tightly correlated with a time trend. Therefore parameter estimates are generally sensitive to changes in model specification and sample coverage (Farrar and Glauber, 1967). Moreover, multi-collinearity coupled with data limitation leads to a tendency to either underspecify or oversimplify the model with consequent biases in regression coefficients (Klein, 1962). According to Taneja (1976), it is difficult to answer the question of how high can the correlation coefficient reach before it is declared intolerable since it varies from case to case, and among different analysts. However he mentions that it is sometimes recommended that multi-collinearity can be tolerated if the correlation coefficient between any two explanatory variables is less than the square root of the coefficient of multiple determination.

When detailing the results of models for Log (RPK 85-2007), in Model 1 and Model 2, the correlation coefficients are respectively 0.9768 and 0.9821 and are both lower than their related R-Squared.

As stressed by Taneja (1976), in air travel demand modelling the main final objective is only to forecast future traffic volumes, and not in the structural relationships among the variables. In such cases, evaluating the overall predictive accuracy of the model is of much more importance than aiming for unbiased, efficient and consistent regression coefficients. Therefore, it is quite possible to use a model knowing that problems such as multi-collinearity are inherent in the model.
However, he specifies that in such cases, it is essential to recognize that the assumption made on the functional relationship observed from the past data will remain valid during the forecast period. Should this assumption not hold, the model cannot be used for explanatory predictive purposes. The validity of this assumption can be investigated by testing for structural stability of the regression coefficients in order to determine whether the parameter vector has been stable over the entire sample. He suggests that in calibrating an air travel demand model based on twenty years of time series data, there is a need to ensure that the assumption on the price elasticity of demand has remained constant during the twenty year period.
Therefore there is a need to test the structural stability for Model 1 as in Model 2 the issue is similar due to the same multicollinearity issue between Real Yields and Real GDP.

In order to perform the test for structural stability, it is necessary to divide the data into two groups and estimate the regression coefficients for each group. For the data related to the EU traffic between 1985 and 2007, 2 sub-groups of data set have been defined: one from 1985 to 1995 and the other from 1995 to 2007. The break point of 1995 has been chosen to be in line with the supply side analysis that will be done starting from 1995 for all types of carriers. In addition, this year is close to the year of the full implementation of the third package and it can be reasonably estimated that a structural change may have occurred with the development of the LCCs.

In order to test the structural stability a Chow test is conducted for Model 1, and 2 unrestricted regressions (Model 1bis and Model 1ter) are estimated for each sub-period separately, in addition of Model 1 which is the restricted regression already estimated for the whole period from 1985 to 2007.
The specifications of Model 1bis and Model 1ter for Log (RPK 85-2007) are shown in Table AC2 of Appendix AC.
The test is in equation (21) comparing RSS to the sum of the residual sum of squares for the two sub-samples, RSS1 and RSS2 of the regressions Model 1bis and Model 1ter, respectively. Based on the number of observations in each group, 11 and 13 respectively and on the total number of parameters which is 3), the Chow test statistic is as follows:

$$\text{Chow}=\frac{(0.049 - 0.0198 - 0.0211) / 3}{(0.0198 + 0.0211)/(11+13 - 2*3)} \qquad (21)$$

$$\mathbf{1.199} \leq F\ (3,\ 18) \qquad (22)$$

The Chow test statistic follows the F distribution with 3 parameters and (11+13-2*3) degrees of freedom.
As shown in equation (22), the F value for the Chow test is lower than the critical value for F (3, 18). Therefore the Null hypothesis cannot be rejected and it can be concluded that the Model 1 including both Real yields and Real GDP as regressors, is stable over all the sample period of 1985 to 2007.

Hence, the potential inability to isolate the separate effects of income, and yields that could derive from multi-collinearity is not a problem in this forecasting exercise with OLS, assuming that their existing linear relationship persists approximately in the forecast period. In this specific case, the out-of-sample forecasts are produced for 3 years after 2007, and it seems reasonable to assume that the relationship between the 2 independent variables is still the same.

The choice of a model depends on the study’s objectives, and as the goal is only prediction, then this multi-collinearity is not a concern to evaluate the forecasting power of the CCI as demonstrated through the efficiency of the model 2 as a predictive instrument.

6.6.5. The OLS regressions in the 1985-2000 time span

The first sets of data used are based the period going from 1985 to 2000, in order to check if including real-time forecasts for all regressors is giving more significant traffic forecasts when compared to actual values from 2001 to 2010. In the stepwise procedure Log RGDP 2000, Log RGDP/Cap 2000, Log RU 2000 and Log RYields 2000 are initially included. The best initial model found is based on Log RGDP 2000 and it will be referred to as Model 1.

When introducing the CCI in the stepwise it did not appear as significant enough to enter the model, should it be with this Model 1 or with the Model 1 bis specified in Appendix AE and based on RGDP/Cap and yields.

The results obtained for the two time series from 1985 to 2010 and to 2000 are different from what has been found in the first case study.

However it is important to test the explanatory power of the consumer confidence in each supply side segment before drawing any conclusion.

6.6.6. The OLS regressions in the 1995-2007 time span

The next step is to assess the sum of each model built for each supply segment, in order to compare it with the global one, both of them built from 1995 to 2007, for comparison purposes. The objective is to check if the out-of-sample data produced for 2008, 2009 and 2010 are more accurate when including the confidence index in the top down model or in the bottom-up one. It would have been also relevant to do the same for the period 1995 to 2000, but the data sample is too small to enable the validation of the results.

When modeling the network segment between 1995 and 2007, and as shown in Table AF1 of Appendix AF, it indicates that model 2 including CCI perform better than model 1 which does not include confidence indicator. Model 2 is showing improvements of the adjusted R-Squared and decrease of RMSE, as well as improvement of the F-value of the model.

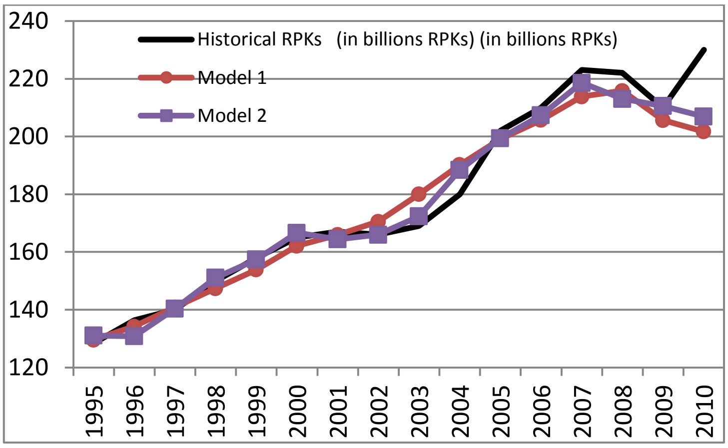
Regarding the assumption on the real network yields decrease between 2007 and 2010 a decrease of 1% per year has been decided, based on the 3.4% average annual yield decrease registered between 1995 and 2007, which represents more than what really occurred, namely a marginal increase of 0.2% on average between 2007 and 2010.

Table 27: Comparison of forecast errors for Model 1 and 2 for the Network segment between 1995 and 2007

Year	Historical RPKs (in billions RPKs)	Model 1	Forecast Error Model 1	Model 2	Forecast Error Model 2
1995	128	130	**1%**	131	**2%**
1996	136	134	**2%**	131	**4%**
1997	140	141	**1%**	140	**0%**
1998	150	147	**2%**	151	**1%**
1999	158	154	**3%**	157	**0%**
2000	165	162	**2%**	167	**1%**
2001	167	166	**1%**	164	**2%**
2002	166	171	**3%**	166	**0%**
2003	169	180	**7%**	172	**2%**
2004	180	190	**6%**	188	**5%**
2005	202	199	**1%**	199	**1%**
2006	210	206	**2%**	207	**1%**
2007	223	214	**4%**	219	**2%**
2008	222	216	**3%**	213	**4%**
2009	210	206	**2%**	211	**0%**
2010	230	202	**12%**	207	**10%**

Besides, when looking at the forecasting errors calculated in Table 27, the forecasts have been improved notably during some of the crises time, namely in 2002, 2003 and 2009, but also during normal periods, in the last decade. As shown in Figure 48, the goodness of the fit of the model is significantly improved by adding the consumer confidence, notably during crisis times, while the out-of-sample data are more accurate when compared to real values of 2009 and 2010.

Figure 48: Goodness of the fit between Model 1 and 2 for Network carriers



The same process was applied to the LCC segment, by introducing the confidence elements in the initial forecasting equation based on the best model selected by the stepwise process, based only on Log Real GDP per Capita 95-07. The confidence index did not appear as significant enough to enter the model.

As a next step, the same process was applied to the Charter segment, by introducing the confidence elements in the initial forecasting equation based on the best model selected by the stepwise process, based only on Log Real GDP per Capita 95-07.

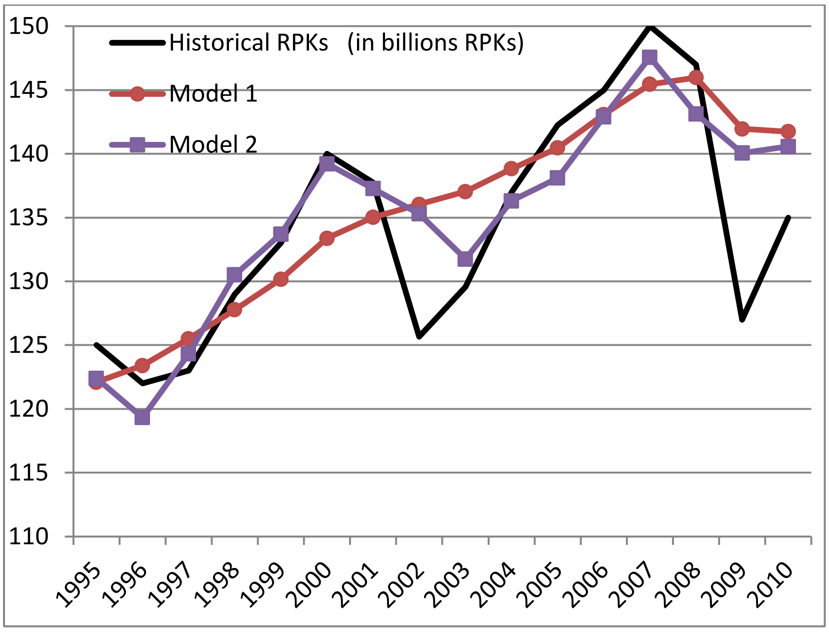
As shown in Table AG1 of Appendix AG, Model 2 which is including CCI is showing improvements of the adjusted R-Squared and decrease of RMSE.

Table 28: Comparison of forecast errors for Model 1 and 2 for Charters

Year	Historical RPKs (in billions RPKs)	Model 1	Forecast Error Model 1	Model 2	Forecast Error Model 2
1995	125	122	**2%**	122	**2%**
1996	122	123	**1%**	119	**2%**
1997	123	126	**2%**	124	**1%**
1998	129	128	**1%**	131	**1%**
1999	133	130	**2%**	134	**1%**
2000	140	133	**5%**	139	**1%**
2001	138	135	**2%**	137	**0%**
2002	126	136	**8%**	135	**8%**
2003	130	137	**6%**	132	**2%**
2004	137	139	**1%**	136	**1%**
2005	142	140	**1%**	138	**3%**
2006	145	143	**1%**	143	**1%**
2007	150	145	**3%**	148	**2%**
2008	147	146	**1%**	143	**3%**
2009	127	142	**12%**	140	**10%**
2010	135	142	**5%**	141	**4%**

The improvements seen with Model 2 compared to Model 1, thanks to the introduction of confidence index, has marginally improved the forecast error in 2001, 2003 and 2009, as shown in Table 28.

Figure 49: Goodness of the fit between Model 1 and 2 for Charters



Generally speaking, between 1995 and 2010, Model 2 for charters is showing a much better goodness of the fit, even during normal times.

Finally, when modelling the global EU traffic from 1995 to 2007 following the same process described before, the best first model (model 1) found is based on Real GDP95-07 and Real Yields, and the second one (model 2) shows CCI significant enough to appear in the model at a second stage. As shown in Table AH1 of Appendix AH, Model 2 improved the Adjusted R-Squared, while decreasing the RMSE.

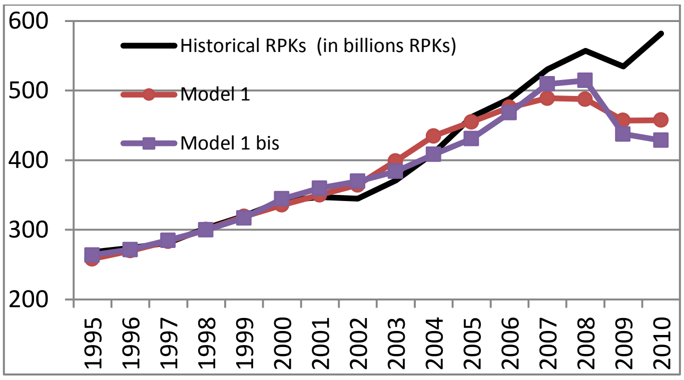
Table 29: Comparison of forecast errors for Model 1 and 2 for Global EU RPKs

Year	Historical RPKs (in billions RPKs)	Model 1	Forecast Error Model 1	Model 2	Forecast Error Model 2
1995	268	258	**4%**	262	**2%**
1996	274	270	**1%**	262	**4%**
1997	281	284	**1%**	281	**0%**
1998	303	300	**1%**	309	**2%**
1999	320	319	**0%**	329	**3%**
2000	341	336	**2%**	345	**1%**
2001	347	350	**1%**	346	**0%**
2002	345	364	**6%**	351	**2%**
2003	371	399	**7%**	381	**3%**
2004	411	435	**6%**	436	**6%**
2005	462	455	**2%**	458	**1%**
2006	488	476	**3%**	482	**1%**
2007	531	489	**8%**	496	**7%**
2008	557	488	**12%**	467	**16%**
2009	535	457	**15%**	453	**15%**
2010	582	458	**21%**	458	**21%**

As shown in Table 29, the variable CCI decreases significantly the forecast error in 2001, 2002 and 2003.

More generally speaking, between 2000 and 2007, Model 2 is performing better than Model 1, as the moves in confidence index are able to reproduce the various peak and troughs of traffic movements during the last ten years. The final step consists in linking all these results in order to establish the method that gives the best forecast accuracy for the global European traffic.

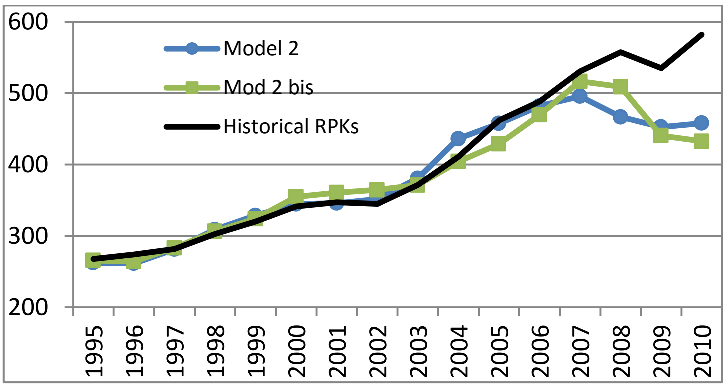
Figure 50: Goodness of the fit between Model 1 and Model 1 bis for the global EU RPKs



When comparing the sum (Model 1 bis) of the best fitting Network, Charter and LCC 95-2007 models (without CCI) to the global (Model 1)best fitting 95-2007 model (without CCI), it appears that until 2007, the sum of the models (bottom-up) has a better goodness of the fit than the global model (Top-down), while the forecasts established by both models are far from the real figures registered in 2008, 2009 and 2010.

Then, it is necessary to perform the same exercise with all the models 2 including the CCI already identified as performing better than any of the models without CCI, except for the LCC segment.

Figure 51: Goodness of the fit between Model 2 and Model 2 bis for the global EU RPKs



The results are inversed when comparing the sum of the models including CCI to the global model including CCI.

The weak performance of the sum of the models is linked to the model attached to the LCC demand, where the CCI has not appeared as significant enough to enter in the model. Therefore, it is biasing the results, showing a bottom-up model less accurate than the top-down one when including the CCI.

The final step compares the average annual traffic growths registered with the ones established by all the models, based on both a segment approach and the inclusion of confidence index. This will enable to test the forecasting accuracy both on a medium and a long term vision, and to determine the method that gives the best estimation for the global EU 15 traffic, from the Top Down or the Bottom-up approaches.

Table 30: Historical vs modelled traffic growth for the EU market

AAGR	Historical traffic	Model 1	Model 1 bis without CCI	Model 2 with CCI	Model 2 bis with CCI
2000-2010	5.5%	3.1%	2.2%	2.9%	2.0%
1995-2000	4.5%	4.4%	4.9%	5.7%	6.1%

Surprisingly the Top Down approach without CCI is showing the greatest forecast accuracy on both a short-term period, 5 years and a longer term period, namely 10 years.

6.7. Conclusions

According to the results of this second case study, confidence appears to be useful to improve models and forecast values for air travel demand, during the last 10 years, and it seems more helpful when periods of uncertainty are covered. In the stepwise process, the value of the CCI has been chosen in priority to other economic variables (excluding GDP or GDP per Capita and yields) to be included in the forecasting equation,

The results found for the network and the charter segments are suggesting that the forecasting power of the confidence index could be linked to the relative maturity of the demand on each segment of this market, compared to the LCC one. This is comforting the results found for the US legacy and Low Cost carriers linking the explanatory power of the Confidence index to the maturity of the supply side segment. However the differences between network, charters and Low Cost carriers are fading away, as a low-cost basis is a necessary tool in the current airlines´ survival kit.

As a next step, and after having studied two intra markets, it is logical to check these results for an international market which could be the US-Europe flow as consumer confidence indices are available in both parts of the Atlantic Ocean.

7. THIRD CASE STUDY: EU-US AIR TRANSPORT MARKET

Air travel between North America and Europe is the third world air travel market in terms of traffic market share, as about 12% of all international air passengers travel between these two continents. In order to better understand the characteristics of this international air travel market, it is necessary to have a closer look at the background of the legal framework and its implications in terms of business model.

7.1. The legal framework

7.1.1. The bilateral system

In most parts of the world, international air services between countries operate under the terms of a bilateral Air Service Agreement (ASA) negotiated between the two countries. These agreements are generally of treaty status The framework for these bilateral ASAs was established towards the end of World War II in 1944, when 52 countries came together at the International Civil Aviation Conference held in Chicago (USA) which established the Convention on International Civil Aviation (commonly referred to as the Chicago Convention).

The Chicago Convention stipulated that two nations seeking to be linked by commercial air services would negotiate the terms through concluding an ASA. This would specify the conditions under which the proposed services would operate in terms of the privileges granted by either signatory country to the airline or airlines of the other country. Initially the bilateral ASAs allow only for restricted flight frequencies, city pairs, and number of aircraft allowed to fly between two countries. The ASAs are based on the nine 'freedoms of the air' designed to provide framework for the principles and arrangements needed for the safe and successful implementation of scheduled international air transport A typical ASA agreement would cover such items as:

a) **Traffic rights**: Also known as *Freedoms of the Air*, these are a standard set of nine distinct air rights over which the two countries will negotiate. As stated in the ICAO *Manual on the Regulation of International Air Transport* (Doc 9626, Part 4), a summary of these nine freedoms of the air are in Appendix AM. ICAO characterizes all "freedoms" beyond the Fifth as "so-called" because only the first five "freedoms" have been officially recognized as such by international treaty. Virtually all bilaterals will allow freedoms one to four. However, bilaterals differ in their treatment of fifth freedom rights (the ability of a carrier from Country A to carry traffic from Country B to a third country as an extension of a service between Countries A and B), as some bilaterals do not permit this type of traffic while others do, or some variant of it.

b) **Authorized points**: The allowable routes that could be operated. This could range from a general statement such as “any point in Country A to any point in Country B” to an exhaustively detailed specification of individual airports, and what points could or could not be combined on a particular flight and in what order.

c) **Capacity**: The number of flights or seats that could be operated between the two countries.

d) **Pricing**: The method for setting fares on the route. The agreement would specify the conditions necessary for a fare proposed by the airline of one country to become operative. Some agreements require airlines to submit ticket prices to aeronautical authorities for approval while others allow the airlines to set prices without restriction.

e) **Designation**: The number of airlines the bilateral partners can nominate to operate services and the ownership criteria airlines must meet to be designated under the bilateral agreement (e.g., the airlines designated by Country A must be majority owned by residents of Country A).

f) **Other clauses**: They are related to operative agreements (e.g. code-sharing) and various “doing business” issues such as repatriation of currencies, the ability to select handling agents at foreign airports and the use of computer reservations systems (CRS).

Historically, many of the bilateral ASAs have been fairly restrictive, as a typical bilateral ASA specifies the limits on pricing, capacity, designated airlines and routes operated. Therefore, the development of international air service has been as much a function of government policy as it has been a function of commercial considerations.The concept of international bilateral aviation agreements has greatly evolved since its inception in 1944.

7.1.2. The liberalization trend

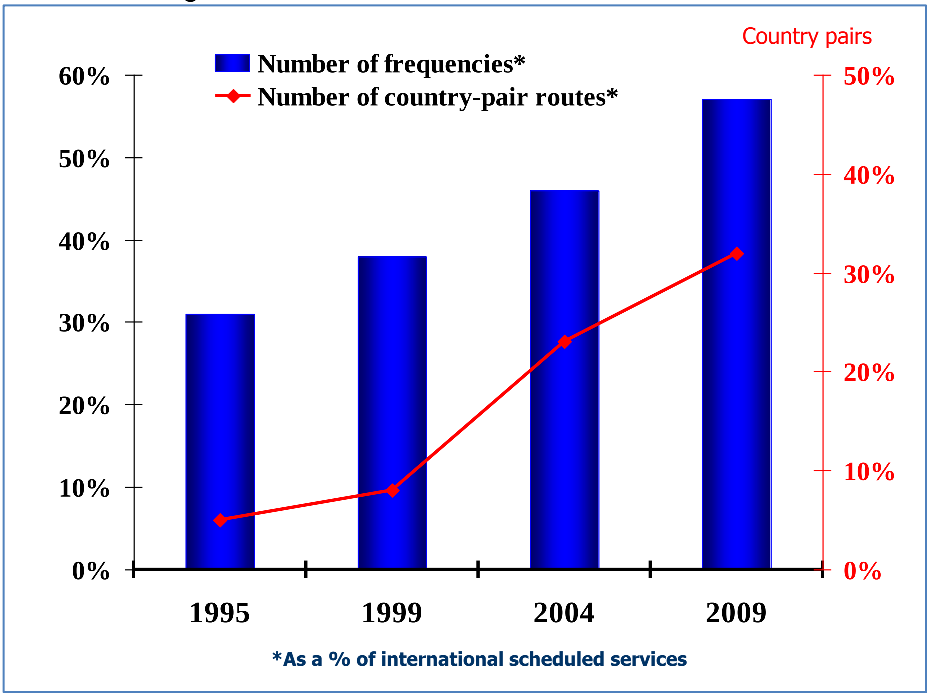
Although the international framework of the Chicago Convention has proven to be fairly flexible, allowing a wide range of ASA structures, from highly restrictive agreements to more liberal ones (allowing notably free entry of airlines of either signatory nation to any route, unrestricted capacity and full pricing freedom), a number of shortcomings have been identified with this form of regulation. Under restrictive ASAs, any change in any clause would require several years before being implemented. Besides, the bilateral negotiations are focused on the benefits to the airlines, while the benefits to passengers and more generally speaking, the wider economy, are given less weight.

In the mean time the air transport industry has undergone considerable transformation which is not always reflected in the ASAs. Technological improvements have allowed a great range of services at much lower cost and many countries have privatized previously state-owned air carriers.

Recognizing these shortcomings and the potential economic benefits of a more liberal aviation sector, many governments have moved to deregulate various aspects of aviation. This has included the privatization of airlines and airports, deregulation of domestic markets and liberalization of ASAs.

The liberalization of international air transport regulation continued to evolve at various levels since the 1980s. According to ICAO (2009), it is estimated that, in 2008, this involved about 31% of country-pairs with non-stop scheduled passenger air services and about 58% of the frequencies offered, through either bilateral “open skies” air services agreements or regional/plurilateral liberalized agreements and arrangements, compared with about 7% and 35%, respectively, a decade ago, as shown in the trend featured in Figure 52.

Figure 52: Trends in liberalization indicators



Source: ICAO

Bilateral ASAs remain the primary vehicles for liberalizing international air transport services for most States.

However, the growth of LCCs and overcapacity in the airline industry has reinforced the need for further liberalization of international air travel beyond that permitted by traditional bilateral agreements.

For this reason, traditional bilateral aviation agreements are becoming more and more out of date and governments have started moving toward agreements with country blocks rather than individual nations to create ´´open skies´´ between geographic regions.

7.1.3. The ´´Open Skies´´ agreement

One notable development is the considerable increase in the number of bilateral “open skies” air services agreements (OSA), which provide for full market access without restrictions on Third, Fourth and Fifth Freedom traffic rights, designation, capacity, frequencies, code-sharing and tariffs. OSAs permit unrestricted international air service between participating countries, allowing each country’s airlines to fly between any city in its home country and any city in participating countries.

The first such agreement was concluded in 1992 between the Netherlands and the United States. According to ICAO (2009), as of March 2009, 157 bilateral “open skies” agreements have been reportedly concluded, involving 96 States (and territories), with the United States being one of the partners in 82 cases. Over 60% of the agreements also grant “Seventh Freedom” traffic rights for all-cargo services (12 agreements granting this right for passenger services, and 10 agreements granting “Eighth Freedom” traffic rights or consecutive cabotage rights for all services, too).

About 35% of the bilateral OSAs concluded by the United States have a transition annex that places limits on or provides for the phase in of, *inter alia*, frequencies, Fifth Freedom traffic rights, Seventh Freedom traffic rights for all-cargo services, code-sharing, non-scheduled services, and ground handling, some of which were applied only to airlines of the United States.

Table 31: Key differences between traditional bilateral agreements and open skies agreements

Type of agreement	**Service capacity**	**Service frequency**	**Fares**	**Extended traffic rights**
Traditional bilateral agreement	Restrictions on which airlines can operate	Restrictions on what markets airlines may serve/number of flights that can be flown	Restrictions on pricing	Restrictions on operations to and from additional countries
Open skies agreements	No restrictions on the number of airlines that may operate, nor restrictions on what markets airlines may serve	No restrictions	No restrictions on pricing	Allowance for open rights to and from additional countries

Source: General Accounting Office (GAO), 2004

In addition to an improved operating flexibility and service expansion for carriers, these agreements also facilitate the scheduling of connecting flights, greater capacity in specific gate-to-gate markets, and potentially lower prices due to increased flight options.

7.1.4. The EU-US ´´Open Skies´´ agreement

Following significant change brought about by the ADA of 1978, the US began engaging Air Transport Agreements in 1979 and by 1982 the US had signed 23 bilateral air service agreements worldwide and soon followed such steps by negotiating OSAs with individual European states during the nineties.

As a result, by 2007, 16 of the 19 European countries offering direct flights to the US had already an OSA with the US, corresponding to a total of 54% of seat capacity across the North Atlantic.

In parallel, negotiations involving a group of States (for example, between one or more States on one hand and a group of States on the other; and between two groups of States) in air service negotiations have introduced a new dimension in international air transport regulation.

In this respect, EU has been the most active by signing at the regional level arrangements for liberalization of intra-regional air transport services, namely, the Single Aviation Market within the EU[37].

In 2003, the Council of EU conferred on the European Commission a mandate to negotiate a comprehensive air services agreement on behalf of all member States with the United States for creation of an “open aviation area” (OAA) between the two territories, as well as a so-called “horizontal” mandate to negotiate with third countries to bring certain specific provisions in the existing bilateral air services agreements in line with Community law. As a result, the US entered negotiations with the EU to specify conditions leading to a community OSA. Among the opposing issues, it is worth mentioning cabotage, antitrust immunity, rules on foreign ownership and EU-US tax issues.

In that context the EU has forced its member nations to abandon existing bilateral OSAs with the US, ruled to be in violation of the exclusive powers of the EU, in favour of one blanket open skies policy between the two continents (Browne, 2005).

After four years of stilted negotiations, EU and US leaders, on 30 April 2007, signed a so-called "open skies" deal, replacing existing bilateral aviation agreements between the US and EU member states.

The main elements of the agreement were related to a removal of restrictions on route rights and cabotage, although it does not allow European airlines to fly domestic US routes. The deal does nevertheless give European carriers the right to establish subsidiaries in the US, which can carry domestic traffic if they meet a number of stringent requirements, but the deal will not compel the US authorities to ease existing rules that prevent European companies and individuals from owning more than a 25% stake of voting rights in US carriers. However the EU obtained a "suspension clause" in the final deal, which commits the US to taking further steps towards opening up its domestic market and loosening its rules on foreign investment and ownership by mid-2010. Under the EU-US Open Skies Agreement, free market competition is encouraged by removing restrictions on international route rights and designated airline numbers, frequencies, capacities, and aircraft types. Any sales, ground handling services, cargo consolidation, and transport may be established in one country by an office in another country. Designated

[37] The liberalization package has been applied also to three member States of the European Free Trade Association (EFTA) belonging to the European Economic Area (EEA) since 1994 as well as Switzerland through a bilateral agreement on air transport since 2002. The Single Aviation Market was further developed to the European Common Aviation Area (ECAA) involving 35 States in 2006

airlines are allowed to create alliances (code-sharing or leasing arrangements) with airlines of either country and with the option to authorize code-sharing between airlines and surface transportation companies. Furthermore, carriers may choose to operate under the charter regulations of either country while agreeing to safety and security standards.

Table 32: Main features of US bilateral ASAs

	Pre-1978 bilateral air service agreements	1978-1991 Open Market bilaterals: US airlines	1978-1991 Open Market bilaterals: Foreign airlines	Post-1991 Open Skies bilateral
Market access	Only to specified Points	From any point in the US to specified points in foreign countries	Access limited to a number of US points	Unlimited
	Limited 5th freedom rights granted to US carriers	Extensive 5th freedom rights granted		Unlimited 5th freedom rights
	Charter rights not included	Unlimited charter rights		
	7th freedom rights not granted			
	Cabotage not allowed			
Designation	Single – some multiple	Multiple		
	Airlines must be "substantially and effectively controlled" by nationals of designated state			
Capacity	Capacity agreed or shared 50:50. No capacity/frequency controls in liberal bilaterals, but subject to review	No frequency or capacity controls		
		Break of gauge permitted in some agreements		Break-of-gauge rights granted
Tarrifs	Approval by both governments (double-approval) or as agreed by IATA	Double-disapproval (filed tariffs operative unless both governments disapproval) or country of origin rules		Free pricing
Code-sharing	Not part of bilateral			Code-sharing permitted

Source: Button, 2008

Following the launch of second-stage negotiations in May 2008, negotiators ended with the initialling of the Second Stage Agreement, on 25 March 2010. On 24 June 2010, a protocol to amend the first-stage EU-US Air Transport Agreement was signed and entered into provisional application. The protocol did not remove the foreign ownership and control restrictions. Both sides did commit to the shared goal of removing market access barriers to maximize benefits, including enhancing the access of airlines to the global capital markets, and the development of a process of cooperation in this regard.

Although the regulatory changes engendered by the EU-US Air Transport Agreement, as amended, are significant, it will nevertheless take several years for the market to adjust fully and to measure any significant further evolution For instance, with fewer regulatory barriers in place for transatlantic air services, more commercial opportunities are created, including those allowing airlines to restructure and adapt to dynamic industry changes. In addition, LCCs may expand their networks or adjust their business models to take advantage of new possibilities, such as the right to operate transatlantic services from any EU city to any US city.

Investment in a long-haul fleet may now be more financially attractive because carriers are no longer limited to nonstop operations from a single Member State. In that context, a possible takeover of Aer Lingus by Ryanair to launch low-cost flights across the Atlantic could be an attempt to establish a long-haul LCC for the EU-US air travel market.

7.1.5. Impact on the airlines' business models

Despite the trend towards liberalization, there remain considerable government restrictions on airline operations and ownership and it is worth noting that many of the remaining restrictions placed on the operation of international air service and the ownership and control of airlines are fairly unique to the airline industry.

These “nationality clauses” impact the carriers that may enter markets and in the US case, it is specifically mentioned that the carrier must be “substantially and effectively controlled” by nationals of the designated state or by its nationals. Linked with this, foreign ownership of carriers operating in US and intra-European markets is also limited, both in terms of the share ownership permitted and the voting power of these shares. For example, the Air Commerce Act 1926 requires that US citizens own at least 51% of any individual aircraft in order for it to be registered under the US and the Civil Aeronautics Act 1938, Congress requires that US citizens own or control at least 75% of the voting interests of US airlines. This makes mergers and cross investment impossible outside of the limits set. In addition, there are also rules regarding cabotage, or eighth freedom rights. In the US, domestic services can only be provided by an airline “established” in the country, while within Europe, because of the sovereignty of each nation, US carriers can fly where they can obtain appropriate fifth and sixth freedom rights carry passengers between states, although not within them.

Taking into account this constraint, the EU-US OSA has removed restrictions governing rates and fares, market entry, and the ways revenues are allocated, but has also permitted the strengthening of various forms of business alliances[38]. The emergence of strategic alliances may be seen as an attempt to circumvent the restriction mentioned above.

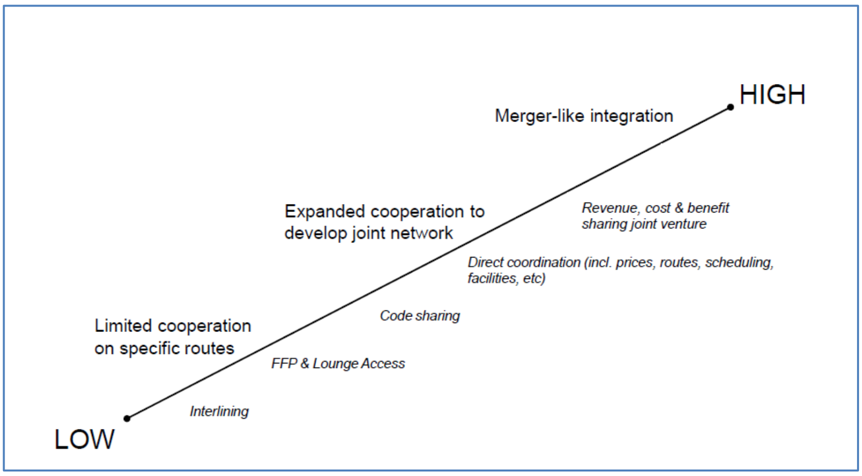
As shown in Figure 53, in a simplified representation, there is a broad spectrum of cooperation by alliance partners, ranging from basic, arms-length arrangements to highly integrated Joint Ventures (JVs).

Since ownership and control restrictions will remain to limit the freedom of carriers to merge and given that alliances result in significant benefits for carriers, global alliances and immunised) JVs seem likely to continue to play an important role in transatlantic markets.

[38] Airlines alliance: voluntary unions of airlines held together by various commercial cooperative arrangements such as code-sharing; blocked space; cooperation in marketing, pricing, inventory control and frequent flyer programmes (FFPs); coordination in scheduling; sharing of offices and airport facilities; joint ventures and revenue sharing; and franchising.

These arrangements between air carriers often include route access and marketing provisions such as code-sharing[39] and joint frequent-flier miles programs (FFP).

Figure 53: Level of cooperation in the various airlines alliances models



Source: DoT, 2000

Carriers participating in a revenue or profit-sharing JV with a grant of antitrust immunity (ATI) from DoT[40] engage in the highest degree of cooperation.

Carriers that do not currently participate in any JV but have a grant of ATI and thus the potential to deepen their cooperation, engage in a medium degree of cooperation.

Finally, carriers in a standard alliance relationship, mostly involving cooperation with respect to FFP, lounge access and code-sharing, engage in the lowest degree of cooperation.

Strategic alliances now dominate international air transportation as they are allowing wider network economies of scope and density on the costs side, and economies of market presence on the demand side (Button, 2008).

They also provide a degree of protection for airlines that would otherwise, in excessively competitive conditions that can emerge in aviation, find it difficult to recover their full costs even if they are highly efficient (Button, 2005). The expansion of alliances is a consequence of airlines' response to, *inter alia*, perceived regulatory constraints (such as bilateral restrictions on market access, ownership and control), a need to reduce their costs, and economic incentives to restructure into larger networks as markets become more competitive.

[39] *Code-sharing* is a common industry practice where one airline offers services in its own name for a particular city-pair, but some, or all, of the transportation is provided by another carrier.

[40] When the alliance agreements are approved, DOT undertakes a second step, in which it decides whether to grant ATI. It is not DOT's policy to confer ATI simply on the grounds that an agreement has been approved as pro-competitive. DOT may, however, grant ATI if 1) the parties to such an agreement would not otherwise go forward without it, and 2) DOT finds that the public interest requires a grant of ATI.

Most notable was the emergence of three “global alliance” groupings based initially on a North-Atlantic axis, which carry together over 60% of the worldwide scheduled passenger traffic:

a) “Star Alliance” founded in 1997 (Air Canada, SAS, Lufthansa, United Airlines);

b) “oneworld” founded in 1998 (American Airlines, British Airways)

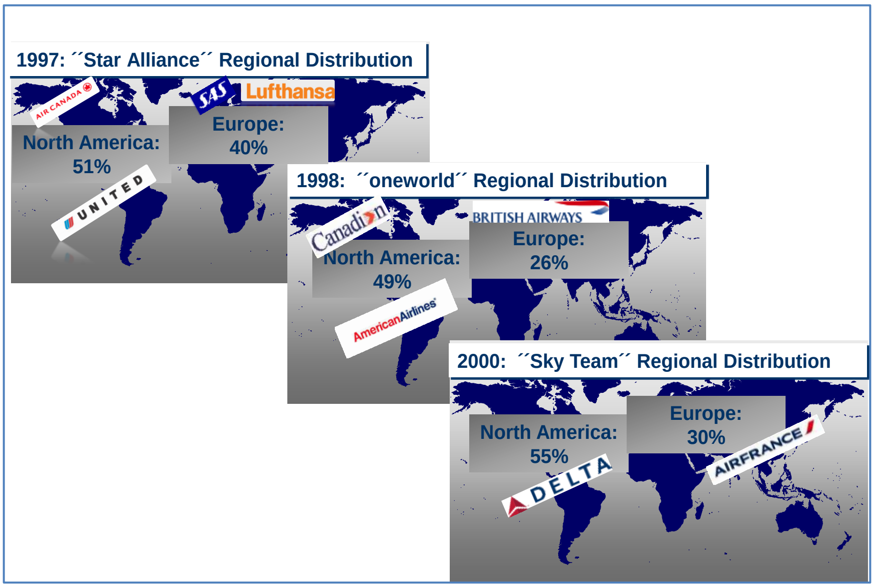
c) “SkyTeam” founded in 2000 (Air France, Delta Airline).

The differing degrees of cooperation within alliances give rise to different types and levels of benefits. Airlines participating in an alliance aim to increase the efficiency of their operations by providing in the same time value to consumers by creating a comprehensive route network, more convenient and better coordinated schedules, single on-line prices, single point check-in, coordinated service and product standards, reciprocal frequent flyer programs, and service upgrade potential.

Alliance partnership with other carriers can also significantly improve access to feeder traffic of alliance partners which is particularly important and relevant for long-haul operations between EU and US, taking into account some restrictions imposed by their OSA.

The main three alliances, One World, Star Alliance and Skyteam are carrying in 2011, about 60% of the world traffic and they were all built around a transatlantic axis between 2 major European and US carriers.

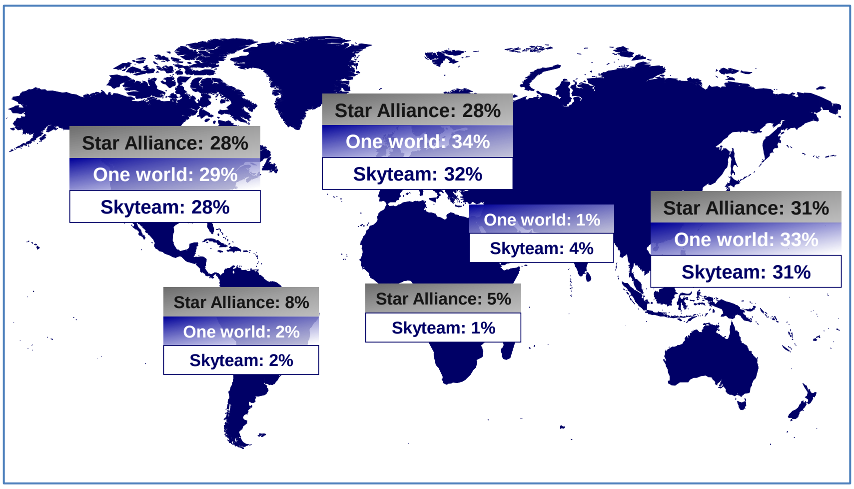
Figure 54: Alliances distribution on the North Atlantic axis (in ASKs)



Source: Derived from OAG data

Each global alliance group remains unstable with partnership relations becoming intertwined and complex. For instance, In 2008, Continental Airlines and United Airlines signed an agreement, which will lead to Continental's exit from SkyTeam and entry into Star Alliance. The shifting development and marketing power of global alliances, together with their competitive consequences, including their dominance at major hub airports, have caused concerns regarding their potential anti-competitive effects.

Figure 55: 2011 Alliances regional distribution (in ASKs)



Source: Derived from OAG data

All the major air carriers deserving the EU-US market belong to one of the three global strategic alliances that dominate the international aviation flights.

Table 33: List of main EU and US airlines deserving the EU-US market and their affiliated alliance

Star Alliance	Oneworld	Sky Team
• Adria* • Austrian • Blue1* • BMI** • Brussel Airlines • Continental • Croatia Airlines • LOT Polish Airlines • Lufthansa • SAS • Spanair • Swiss • TAP Portugal • United • US Airways	• American Airlines • Air Berlin • British Airways • Finnair • Iberia	• Air Europa • Air France • Alitalia • Czech Airlines • Delta Airlines (incl Northwest) • KLM • TAROM

*Under code-sharing arrangements *Source: Airlines alliances sites*
**BMI will begin transitioning into the Oneworld alliance in 2012

However, the alliances have been closely monitored and reviewed by relevant regulatory and competition bodies and, in some cases, certain regulatory measures were introduced to mitigate the potential anti-competitive effects. In 2006, DOT dismissed the original application for antitrust immunity for an alliance agreement amongst six airlines of SkyTeam, and in 2008 approved it under the limitation to transatlantic routes. The European Commission also expressed its concerns that the cooperation of eight airlines of SkyTeam may have a negative impact on competition on several routes.

7.1.6. The recent industry trends

For about 60 years, most of the inter-airline activities such as multilateral tariff setting, establishment of agency systems and service standards, and schedule/slot coordination have been traditionally carried out at the industry-wide level through the IATA conference machineries. However, the scope of the IATA process in the EU-US market was diminished in 2007, when the US DoT decided to withdraw its approval of, and ATI for, IATA's tariff conference discussions and agreements on fares and rates.

At the same time, similarly, the EC decided to end the block exemptions granted for IATA's passenger tariff conferences for the EU–United States routes.

In the last decade, the pace of mergers and acquisitions or operational integration under a single holding company has accelerated in both the EU and the US and most of them have been achieved within the same country or inside the EU. The common objective of this trend is the need to remain competitive. A merger with a competitor may serve to hold and develop the market presence, gain access to new markets, achieve cost savings especially in response to the sharp increase in fuel prices and the LCCs competition. It allows also airlines to shield themselves against competition through the reduction of capacity on the overlapping routes, thus increasing their yields.

The most recent cases in Europe are:

a) Air France and KLM Royal Dutch Airlines created the Air France-KLM Group under a single holding company through a share exchange offer by Air France for KLM's shares in 2004;

b) Lufthansa took over Swiss in 2005 through AirTrust, in which Lufthansa initially had a 49% shareholding and increased to 100% in 2007;

c) Lufthansa acquired 55% of Brussels Airlines in 2011 and took over up to 100% of the shares in Austrian Airlines through its subsidiary company;

d) In 2010 Iberia and British Airways concluded their merger

In US the following mergers have also created strong airlines poles:

a) In 2005 between US Airways and America West

b) In 2009 between Delta and Northwest

c) In 2010 between United Airlines (UAL) and Continental

Table 34: Market share of the passengers carried on the Transatlantic by each major alliance

	Star Alliance	**Oneworld**	**Sky Team**	**TOTAL**
Transatlantic passengers carried in 2009 (millions)*	8.85	5.36	6.66	**20.9**
Market share of each alliance in transatlantic market*	37.6%	22.7%	28.3%	**88.6%**

Source: DoT, 2000

**Onboard (non-stop segment) data for Year Ended June 2010. The alliance shares include all allied carriers operating between the US and the Member States of EU, plus Switzerland and Norway.*

In 2009, according to DoT, non-aligned carriers account for 2.70 million passengers carried or 11.4% of the market. On the North Atlantic market and as of 1 November 2010, the state of cooperation among the members of the global alliances is as shown in Table 35.

Table 35: Level of cooperation between EU and US airlines on the North Atlantic air travel market

	Star Alliance	**Oneworld**	**Sky Team**
High level Of Cooperation	3 members – **Air Canada**, **Lufthansa** and **United-Continental** (integrated JV)	3 members – **American**, **British Airways** and **Iberia** (integrated JV)	3 members – **Air France-KLM**, **Alitalia** and **Delta** (integrated JV)

Source: DoT, 2000

On the North Atlantic, the core members of the global alliances have deepened their cooperation by launching highly integrated JVs. Their stated goal is to become effectively indifferent to which plane or “metal” carries a passenger, i.e. they seek “metal neutrality” in their cooperation.

This form of cooperation is effectively a close substitute to a merger because it typically involves full coordination of the major airline functions on the affected routes, including scheduling, pricing, revenue management, marketing, and sales.

The implementation of the second stage of the Air Transport Agreement is not yet fully operational and the emergence of new business practices and industry trends in the aviation marketplace should continue to interact and have implications on air travel demand between EU and US.

7.1.7. Impact on the EU-US air travel market

Under the OSA framework coupled with the alliance effect, the removal of both the capacity constraint and the negotiated pricing resulted in competition for air services, and a move toward cost reduction of the carriage, thus reducing fares (Button, 2008).

There is both the impact of the combined pressure of both free airline markets across the Atlantic and within the two feeder markets at either end. This combination has also stimulation effects on the demand side, as it increases the geographical market being serviced.

The outcome of the lowering of costs and the outward shift in demand is impacting air travel demand and hence the number of passengers traveling between EU and US increases.

However, due to the free market conditions, fares might not actually fall but rather may rise. The outward shift in demand reflects a better quality of service, through more convenient flights, transferability of frequent flier miles, and seamless ticketing for which, potential travelers are willing to pay more.

In the mean time, the fare structure is influenced by the market power of the airlines on this specific market which is served by a relatively small number of network carriers, and where a degree of competition exists only between the various alliances for the trunk hauls market, notwithstanding that there is also competition at either end of routes with many other, including LCCs, competing for passengers in overlapping feeder and origin-destination traffic to international hub airports.

Several studies have been conducted on the impact of strategic alliances on the North Atlantic routes, focusing mainly on the implications for the airlines involved, their competitors, and the traveling public.
In the literature review related to the effects of alliances on airlines´ profitability the quality of service, the fares and the increase of traffic, the findings are quite mitigated.

In the case of the alliance British Airways (BA)/US Air and KLM/Northwest (NW) for the year 1994, it was found (Gellman Research Associates, 1994) that the profits increased for all parties with BA and KLM gaining more than their partners. For the SAS/Swissair alliance, the results showed that between 1989 and 1991, there were increases in flight frequency, variations in fare levels and the strongest service levels had the lowest fare increases.

In the 1995 US GAO study, it was found that in 1994, for all the carriers partners in the studied alliance (KLM/NW, US Air/BA, UAL/LH, UAL/Ansett and UAL/BMA), they have enjoyed increased revenues and traffic which were gained at competitors´ expense without any industry growth.

When studying the alliances between 1987 and 1991 of Continental/SAS Delta/Swissair and KLM/NW, the results (Dresner et al, 1995) showed that in general alliances did not benefit partners with mixed successes with traffic volumes.

For the alliances studied by Park (1997) between 1990 and 1994 (KLM/NW, Delta/Swissair/Sabena), he found that the traffic increases at the expense of rivals, while fares were lowered by complementary alliances and increased by parallel alliances.

Finally between 1992 and 1994, for the carriers of Star Alliance and oneworld, it was found (Oum et al, 2000) that the traffic increased on alliance routes.

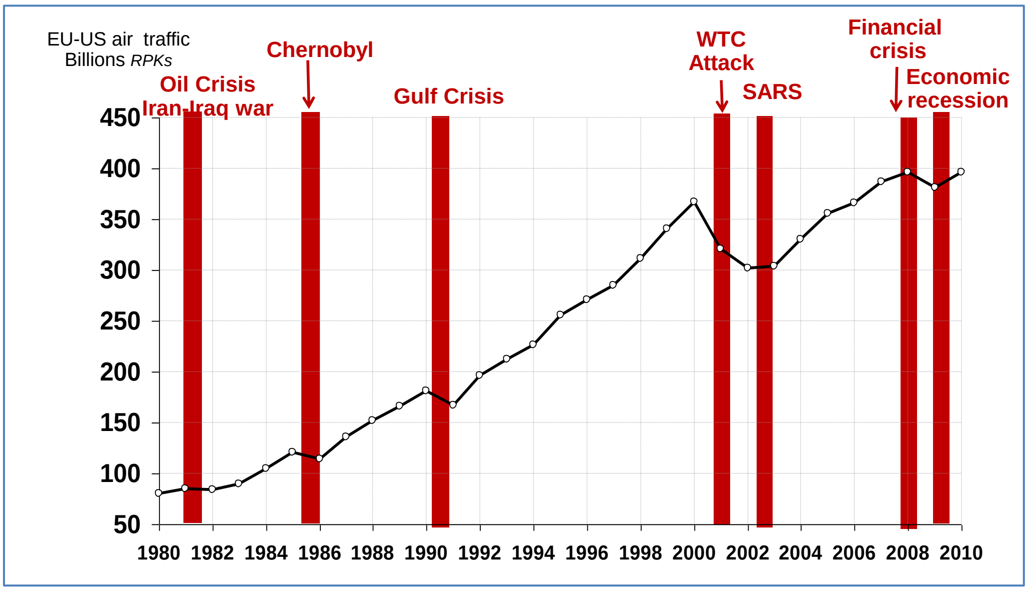
Through product differentiation such as different airports hubs exists in each side of the Atlantic, each alliance has some degree of monopoly power. This could lead to higher fares and a smaller air travel demand. However, the lack of a fully liberalized EU market, prior to the mid-nineties, also added constraints to what could be achieved in the transatlantic market, in terms of traffic growth.

7.2 Market characteristics and growth pattern

7.2.1 Factors and constraints to growth

Air travel between the United States and Europe has been adversely affected (Moss et al, 2008) by terrorist threats both in Europe and the US (2004 train bombings in Madrid, 2005 London bombings, 9/11 and the war in Iraq), global economic turmoil, pandemic outbreaks such as SARS as well as the negative impact of the Chernobyl catastrophe.

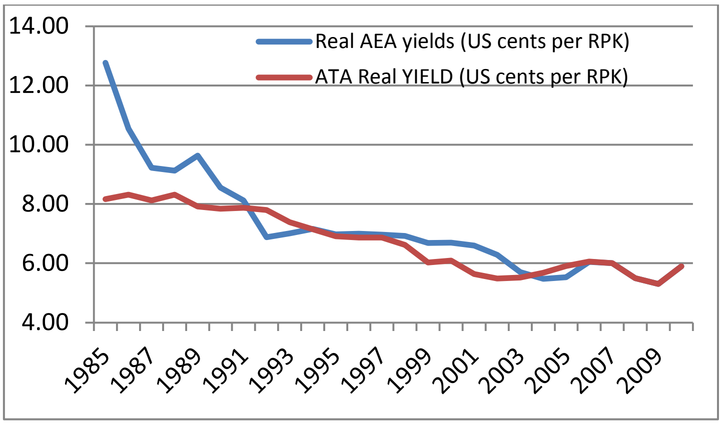
Figure 56: Events that have constrained air traffic growth between EU and US



Source: ICAO

On the other side, several factors contributed to the tremendous growth in the EU-US air traffic that occurred until 2000 including: aviation industry deregulation and privatization, global alliance formation among air carriers, strong economic growth, and increasing trade during the nineties, thanks to globalization. The analysis of the traffic pattern between the successive 10-year periods, since the eighties, has shown obviously different growth rates ranging from a high 8.5% between 1980 and 1990 to a low 0.8 % between 2000 and 2010, as the WTC attack and lately high oil prices combined with the financial crisis are among the forces that have constrained the transatlantic air travel demand.

Figure 57: Comparison of Real ATA and AEA yields on the transatlantic market



Source: ATA and AEA

In a 2000 study conducted by the Office of Aviation Analysis, US DoT examined global aviation alliances and found a marked increase in service to and from smaller markets and decreased fares on routes that included alliance gateways. The report found also that the number of markets and city-pairs served by alliances has increased greatly, offering more choices and travel flexibility for customers.

When comparing the real yields for the AEA and the ATA airlines on the Atlantic route (Figure 57), they seem to follow the same path since notably the early nineties, reflecting the hidden impact of the alliances on the fares applied by the major airlines operating on this market.

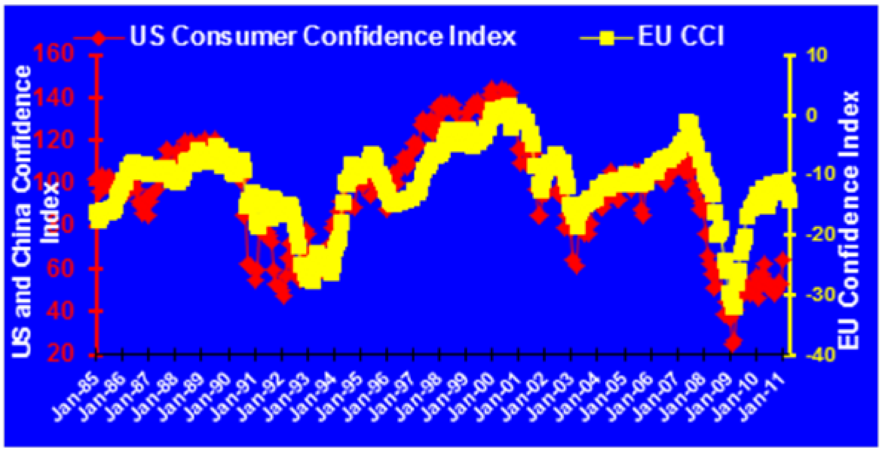
However, the full effects of the EU-US Agreement cannot yet be assessed. The major forces that are enabling to assess whether the patterns of a specific market has changed is linked above all to its regulatory status. Indeed, the Air Transport Agreement between US and EU is quite recent, but it is necessary to keep in mind that US was used to have an open-skies agreement with several European countries. An open skies agreement between the US and the EU is expected to result in additional competition and hence lower fares for passengers leading to a new pattern of traffic growth in the transatlantic market.

7.2.2 Air travel demand levers in the US-EU market

In the North Atlantic market, the great majority of the travellers are non-business travellers. About 46% of all passengers are vacation travellers, 34% are travelling for VFR purposes and only 20% are business travellers. Besides, there is considerable seasonable variation in the demand for air travel in this market, the peak season being the summer. About 40% of all traffic in this market occurs in the third quarter of the year. Finally, when comparing the evolution of the two confidence indices they are quite similar.

Various factors beyond the cost of a seat are driving the US-EU air travel market. Continuing worldwide population growth is critical to growing air carrier demand, but only if sustained by an associated, and parallel, economic vitality and growth. An aging population in well-developed countries with an associated segment growth of wealth also plays an important role in generating discretionary leisure air transportation demand. In addition, business travel demand is driven by healthy, and growing, worldwide economies. The United States is an urbanized nation, with more than 80% of the population residing in cities and suburbs. It is projected to reach 335 million in 2025 and 439 million in 2050, which is a 44% increase from 2008 compared to the UN projection of a world population increase of 37% for the same period. The population in the European Union is expected to increase and reach 470 million in 2025. It is forecast that a reduction of the EU population will occur after 2025 to 450 million in 2050. Based on these respective population growth projections over the next 40 years, traffic growth between EU and US can be expected, while it would appear that the US-EU markets would mature prior to other high growth markets such as the Asian ones.

Figure 58: Comparison of the EU and US Consumer Confidence indices



Source: European Commission and IHS/Global Insight

Unexpected high jet fuel prices could very likely have a negative impact on the frequency and number of flights in North Atlantic airspace. Prior to the fall of 2008, large discrepancies in operating profits and losses for the domestic and international operations of large network airlines were beginning to force commercial carriers out of the domestic market and toward international routes. This shift in network preference was coupled with the decline in short haul markets and increased competition with LCCs. Unfortunately, the cost of fuel remains a huge unpredictable factor and according to IATA, past escalations in jet fuel costs were countered (among other factors) by resilient consumer confidence indices.

In the case of EU and US, the two consumer confidences indices seem to follow the same path (as sown in Figure 58), although in some years the trend appear as being delayed by one or more lags.

7.2.3 Data availability and time span definition

Traffic flows data have been extracted from the ICAO database by aggregating the various city-pairs between USA and the EU 15 States. To stay consistent with the two previous case studies, the time span considered will be 1985-2010. Dummy variables have been identified for the years showing a significant decrease in growth, namely, 1986,1991, 2001, 2002 and 2009. Regarding the macro economic variables, and in addition to the economic variables already taken into account in the two previous case studies (for each region), aggregated variables have been computed.

With regard to the aggregation between EU and US economic variables, the following formula shown in equation (23) is used for GDP, Income and Trade, represented by $(\mathrm{Y_i})$.

$$\ln \mathrm{Y_{Aggregated}} = \sum_\mathrm{i} \overline{w_\mathrm{l}} \ln \mathrm{Y_i} \qquad (23)$$

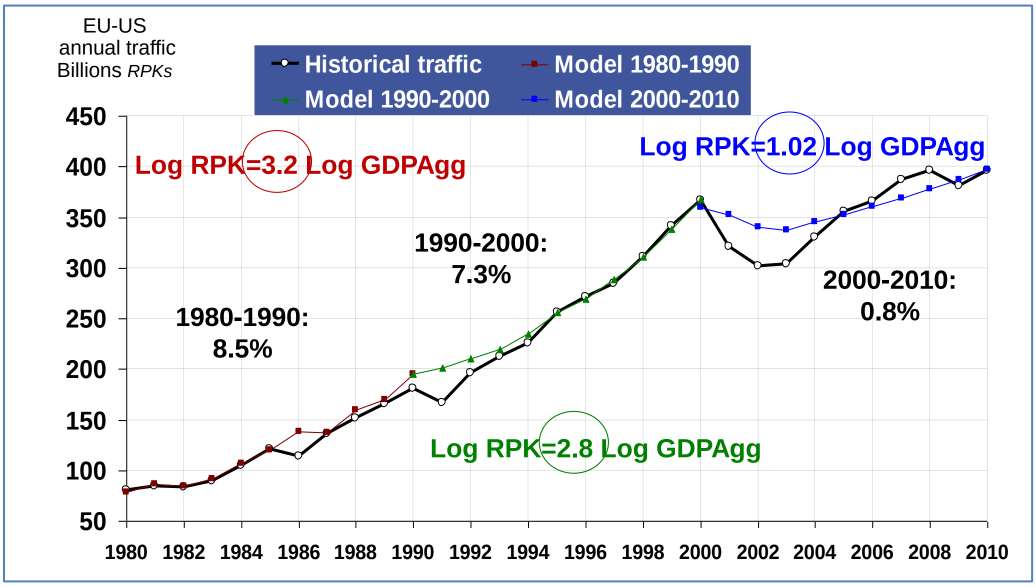
Hence aggregate variable is the weighted sum of the region economic variable for Real GDP, Real GDP per Capita, Rate of Unemployment, Real Trade and confidence indices. In addition RGDP Agg and RGDP/Cap Agg at Purchasing Power Parity (PPP)[41], as well as the Euro/US dollar exchange rate have been added as potential explanatory variables. The real yields taken into consideration are those of the ATA and AEA airlines on the Atlantic route.
The confidence indices have also been aggregated. It is noteworthy that the EU CCI has not the same scale than the US one, as it can take negative values. Therefore (as it was also done for the second case study), a constant variable equal to 100 has been added to each value of the EU CCI.

7.2.4 Level of market maturity and fares trends

Modeling the traffic between three successive 10-year periods, since 1980, has shown changes in the elasticity to the aggregated income, moving from 2 (between 1990 and 2000) to 1 (between 2000 and 2010).

[41] PPP is a theory which states that exchange rates between currencies are in equilibrium when their purchasing power is the same in each of the two countries

Figure 59: Evolution of income elasticities between 1980 and 2010



It is expected that the newly signed OSA will prompt the emergence of new airlines on the EU-US market, leading to a stimulated traffic growth and increased income elasticity, confirming therefore that this air travel market is still not a mature one, despite the income elasticity of around 1 registered in the last decade. This means that starting from 2010, a structural break may appear, giving the birth to a ´´new´´ product for the EU-US air travel market.

Table 36: Price elasticities of air travel demand in the North Atlantic market between 1990 and 2000

Route	Price elasticity
United States to or from Europe	-1.2
Canada to or from Europe	-0.8

Source: Lockheed-California Company

The demand for air travel in this market has been extensively analyzed, in order to determine the price and income elasticities for such air travel demand, including the basis for the purchase decision process.

The traveller choice is based on first differentiating item: if core services (schedule, aircraft, price) are similar, it is the service elements (seat comfort, FFP, added services, etc.) that is the basis of the purchase decision (Guillibaud and Bond 1997). According to Mason and Dudley (2006), price is the key purchase factor for North American business travellers, while FFP point accumulation and reward is still a strong purchase factor. For European travellers, ticket flexibility adds to service package attractiveness. The trend

Premium Economy products can be constructed to be highly attractive to both N. American and European travellers.

In the last 5 years, there was a change in the market offer to answer the decreasing of the full Business Class demand. The development of a new class of service, the Premium economy is part of this answer proposed by the airlines to the passengers.

7.3. The supply side segmentation

The introduction of Advanced Booking Charter (ABC) flights was an attempt by the airline industry and the aviation authorities in Europe and North America to propose transatlantic air travel at fares below the former official IATA minimum fares.

However, the subsequent introduction of Laker Airways' "Skytrain" operation on key transatlantic routes between the UK and the US as well as the competitive response that was triggered from other airlines, resulted in a growing range of low fares being offered on most scheduled services on a year-round basis. This undermined the long-term economics as well as the popularity of ABC flights to such an extent that these flights ceased to be viable by the mid-eighties.

Besides, in a recently observed trend, passengers tend to make their own travel arrangements and travel independently, rather than go on package or inclusive tours.

Table 37: EU-US traffic breakdown by segment

Year	Total traffic Billions RPKs	Network traffic	Charter traffic	Charter market share
1985	121	112	9	8%
1986	114	103	11	11%
1987	136	131	5	4%
1988	152	144	9	6%
1989	166	152	14	9%
1990	181	165	16	9%
1991	167	160	7	4%
1992	196	187	8	4%
1993	212	199	13	7%
1994	226	206	20	9%
1995	256	215	41	19%
1996	271	228	43	19%
1997	285	247	38	15%
1998	311	267	44	16%
1999	341	294	47	16%
2000	367	322	45	14%
2001	321	292	29	10%
2002	302	290	12	4%
2003	304	288	16	6%
2004	330	317	13	4%
2005	356	331	25	8%
2006	366	341	25	7%
2007	387	367	20	5%
2008	396	380	16	4%
2009	381	361	20	6%
2010	396	367	29	8%

Source: ICAO, AEA and Form41

Since the data cover the air passenger traffic carried on scheduled services, changes in air transport regulations make it difficult to classify traffic as scheduled or non-scheduled[42]. Therefore, some changes in the data breakdown could be due to differences in classification.

This can be clearly observed in Table 37, showing an estimated evolution of the market share between the traffic carried by the network carriers and the traffic carried by the charter airlines.

The traffic carried by the network carriers has been estimated by adding the traffic registered on the North Atlantic segment by the AEA carriers and the traffic registered in Form41 on the Atlantic segment.

Then, the charter traffic has been deducted by taking out from the whole EU-US traffic the network traffic. The hectic evolution of the traffic attributed to the charter airlines is throwing some doubts on the reliability of this calculation method as well as confirming the limitation of the data set used.

Taking into account the specificities of this market which is moving toward a new scheme during the next decade, this third case study will only focus on the global EU-US market without analyzing the supply side segmentation due to a lack of availability of historical data.

It is noteworthy that the LCCs market share on this market has been more or less stable at 1% between 1995 and 2010, while even in the ICAO database there is no global data on this market regarding the non-scheduled carriers market share.

7.4. Models, forecasts and results

7.4.1. The OLS regressions in the 1985-2010 time span

When modelling the EU-US traffic between 1985 and 2010, Model 1 as shown in Appendix AI, based on aggregated EU-US income in real values (RINCAGG) has been selected.

Based on this model and leaving in the stepwise process the same regressors than the ones in Model 1, the CCI is introduced in the stepwise box. The stepwise results are showing that Log CCI is not significant enough to enter the equation. It is noteworthy also that when introducing dummy variables as identified in a previous paragraph, the Dummy is not appearing as significant enough to enter the model.

Therefore the same exercise is repeated with a Log RPK data series from 1985 to 2007. The new Model 1 specifications are based on the EU Real GDP per Capita at PPP, and when introducing the Aggregated Consumer

[42] As per ICAO definition in the glossary of ICAOdata+ http://www2.icao.int/en/G-CAD/Pages/glossary.aspx, non-scheduled flights are Charter flights and special flights performed for remuneration other than those reported under scheduled flights. They *include* any items related to blocked-off charters and *exclude* air taxi, commercial business aviation or other on demand revenue flights. Scheduled flights are defined as flights performed for remuneration according to a published timetable, or so regular or frequent as to constitute a recognizably systematic series, which are open to direct booking by members of the public; and extra section flights occasioned by overflow traffic from scheduled flights.

Confidence Index in the stepwise process, it appears as significant enough and builds the Model 2.

Models 1 and 2 are displayed in Table AJ1 of Appendix AJ.

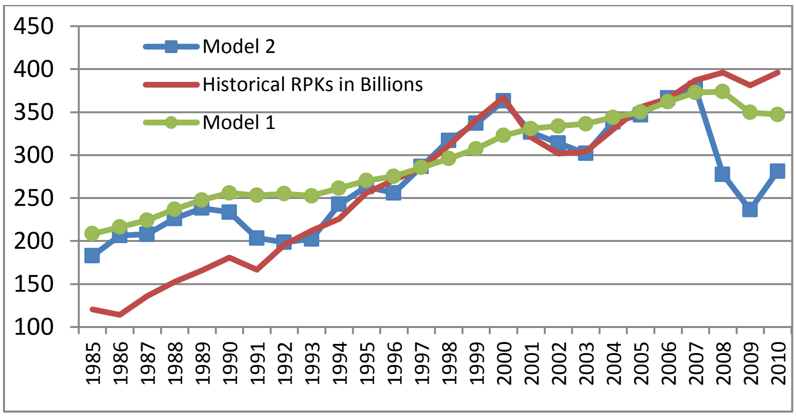
The Adjusted R-Squared is improved significantly, while similarly the RMSE is decreasing sharply.

Table 38: Forecast errors for Model 1 and 2 for Log RPK 85-2007

Year	Historical RPKs (in billions RPKs)	Model 1	Forecast Error Model 1	Model 2	Forecast Error Model 2
1985	121	208	**73%**	183	**52%**
1986	114	216	**89%**	206	**81%**
1987	136	224	**65%**	208	**53%**
1988	152	237	**56%**	226	**48%**
1989	166	248	**49%**	238	**44%**
1990	181	256	**42%**	234	**29%**
1991	167	253	**52%**	203	**22%**
1992	196	255	**30%**	199	**1%**
1993	212	253	**19%**	202	**5%**
1994	226	262	**16%**	243	**7%**
1995	256	270	**6%**	263	**3%**
1996	271	275	**2%**	256	**6%**
1997	285	286	**0%**	287	**1%**
1998	311	296	**5%**	317	**2%**
1999	341	307	**10%**	337	**1%**
2000	**367**	323	**12%**	363	**1%**
2001	321	331	**3%**	327	**2%**
2002	302	334	**11%**	314	**4%**
2003	304	336	**11%**	302	**1%**
2004	330	344	**4%**	338	**3%**
2005	356	350	**2%**	347	**3%**
2006	366	362	**1%**	367	**0%**
2007	387	373	**4%**	378	**2%**
2008	396	374	**6%**	278	**30%**
2009	381	350	**8%**	236	**38%**
2010	**396**	347	**12%**	281	**29%**

Both Model 1 and 2 are not accurate at all for the 1980-1990 period while the model 2 including the confidence index is performing much better than Model 1 in crisis time except for 2008 and 2009.

Figure 60: Comparison of goodness of fit between Model 1 and 2 for Log RPK 85-2007



Model 2 has a very good fit between 1992 until 2007. Once again the issue of accurate forecasts for confidence indices is raised, as obviously they were wrongly established for 2008, 2009 and 2010.

7.4.2. The OLS regressions in the 1985-2000 time span

The second sets of data used are based on the period going from 1985 to 2000, in order to check if including real-time forecasts for all regressors is giving more significant traffic forecasts when compared to actual values from 2001 to 2010.

The two initial models found through the stepwise procedure for Log RPK 85-2000, were based on Aggregated income and Real AEA yields and on Real aggregated GDP and exchange rate. However the confidence index has not appeared as significant enough to enter any of these 2 models.

The details of these 2 models are shown in Table AK1 of Appendix AK.

In light of these results it has been decided to model a data series from 2000 to 2010.

7.4.3. The OLS regressions in the 2000-2010 time span

The model 1 found was based on the aggregated Income and the CCI was found significant enough to enter the model 1 and builds a model 2, as shown in Table AL1 of Appendix AL.

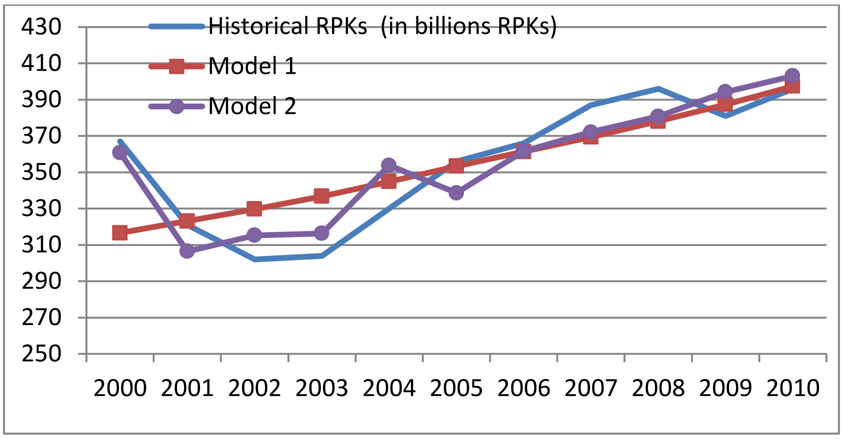
The introduction of the confidence index has significantly increased the Adjusted R-Squared and decreased the RMSE.

Table 39: Forecast errors for Model 1 and 2 for Log RPK 2000-2010

Year	Historical RPKs (in billions RPKs)	Model 1	Forecast Error Model 1	Model 2	Forecast Error Model 2
2000	**367**	317	**14%**	361	**2%**
2001	321	323	**1%**	306	**5%**
2002	302	330	**9%**	315	**4%**
2003	304	337	**11%**	316	**4%**
2004	330	345	**5%**	354	**7%**
2005	356	353	**1%**	339	**5%**
2006	366	361	**1%**	362	**1%**
2007	387	369	**5%**	372	**4%**
2008	396	378	**5%**	381	**4%**
2009	381	387	**2%**	394	**3%**
2010	**396**	397	**0%**	403	**2%**

Model 2 is performing slightly better than Model 1 in 2002, 2003 and 2008.

Figure 61: Comparison of goodness of fit between Model 1 and 2 for Log RPK 2000-2010



As shown in Figure 61, the results are mitigated as the goodness of the fit is not good enough for the Model 2 to enable drawing any relevant conclusion.

Besides the short length of the data series is not allowing to validate the results, although similar trends to the ones found in the previous case studies were found.

7.5. Conclusions

In this third case study, though consumer confidence indexes in some specific time-span are significant in sample using latest-available data, there is no clear evidence that the use of such indexes improves short-term traffic forecasts significantly, as it appears that the main issue is linked to the quality of the forecasts of the consumer confidence indices, as already mentioned for the previous case studies.

According to the results obtained for this third case study, confidence appears to be useful to improve slightly the existing models, without giving an appropriate goodness of fit, as it was witnessed for the first and the second case studies.

8. CONCLUSIONS AND RECOMMENDATIONS

8.1. Conclusions

In many air transport presentations, there are references to the correlation between confidence and traffic growth (e.g. Swan, 2005) but however, there was no available literature that clearly tried to define the exact relationship between air travel expenditures and consumer confidence.

Before this research had been conducted, there was no text available in the literature, on the net benefits of including the Consumer Confidence Index in an air travel demand forecast equation.

Indeed, the case study, conducted by Pegasus Intellectual Capital Solutions for Northwest airline, which has identified Consumer Confidence as a demand driver of the commercial aviation industry is not detailed enough (in the version that could be accessed to the public) to enable straightforward conclusions. In the description of their analysis, it is indicated that they have used longitudinal/time series analysis of a composite of the industry, and then applied multivariate regressions to identify economic drivers of demand, in order to measure their relative contribution to changes in air travel demand. However, there are neither details on the number of observations used, nor the exact values of the parameter estimates. It was also mentioned that the confidence index has been used for the whole traffic of Northwest, meaning Domestic and International segments.

Economic growth is the main driving force, and any increase in GDP usually entails a more than proportional increase in traffic. Conversely air travel demand is very sensitive to recessions, and in line with the accelerated pace of liberalization in most of the world air travel markets, income elasticity of demand for air transport is increasing in the great majority of the markets. Therefore fluctuations in the economy result in even wider fluctuations in the aviation industry, and as air transport is becoming more and more a highly cyclical industry, the confidence index, thanks to its high moves, is identified as a potential suitable factor able to help determining more accurately air travel demand.

In the three case studies, related to the Domestic US, the European and the EU-US air travel markets, the same methods were used to investigate whether or not indexes of consumer confidence are helpful in improving forecasts of air travel demand. It is worthwhile mentioning that the characteristics of the above mentioned air travel markets are moving from a pure Domestic segment (US Domestic), going through a mix of Domestic and International segments (European market) and ending with a full International market (EU-US).

The results obtained for the Domestic US and the European air travel markets showed that the consumer confidence index has some ability to improve the forecasting accuracy of the forecasting models.

According to the results obtained for these two case studies, confidence appears to be useful to improve models and forecast values for air travel demand during the last 10 years, while confidence indices appear to be more helpful when periods of uncertainty are covered.

In the stepwise process, the value of the Consumer Confidence Indices has been chosen in priority to other economic variables (excluding GDP or GDP per Capita and yields) to be included in the forecasting equation for air transport.

More specifically, for the Domestic US market analysis, in the stepwise process, the value of the Current component of the confidence index has always been chosen in priority to be included in the forecasting equation, preferably to the Expected component or to the global value of the Confidence Index. This may indicate that the actual mood of the consumers is playing a bigger role in their air travel spending decisions, at least when referring to the cultural and psychological side of the characteristics of the American passenger.

It is noteworthy that this finding cannot be tested for the European market as the Current and Expected components of the Confidence Index are not available in the European context.

However, although, the addition of the Confidence index increases the goodness of the fit, none of the confidence indices seem to have an explanatory power by itself, regarding air travel demand forecast, in the absence of macroeconomic variables. Nevertheless, it could supplement other explanatory variables such as income, price, availability of alternative transport modes, migration flows and cultural attitudes.

It was also found that consumer confidence indexes are significant for in-sample forecasts, using latest available data, as well as in some out-of-sample forecast models. Indeed, when the indexes of consumer confidence were introduced in the models based on latest available data they were found quite significant enough for air travel demand modeling. However when using data that were available to forecasters in real time, the traffic forecasts that have been produced in this research are not indicative of the value of the consumer confidence indexes in actual forecasting.

There is no clear evidence that the use of such indexes improves short-term traffic forecasts significantly, as it has been highlighted that the main issue is linked to the quality of the forecasts of the consumer confidence indices.

In parallel to this global approach, a more in depth analysis was conducted on the demand forecast linked to the different segments of the supply side, namely Legacy (including Regional) and Low Cost Carriers for the US market, and Network, Charter and Low Cost carriers for the European one. Through that further study, consumer confidence appeared as a statistically important determinant of air travel demand, especially for Legacy, Network and Charter carriers, in periods of elevated uncertainty, as it was the case in the 1991-1992 crisis or in the aftermath of the 2001 attack, as well as in 2008 and 2009.

The results found for the Legacy, Network and Charter segments are suggesting that the explanatory power of the confidence index could be linked to the relative maturity of the demand on each segment of this market, compared to the one related to the LCC segment.

In the coming years, and due to the airport capacity constraints at the major hubs, the network expansion on both the Domestic US and the European air travel markets can only be accommodated by the LCCs, thanks to their business model. As most of the LCCs are choosing to fly to secondary airports, the network development is and will be made through the routes opened by LCCs, taking also into account the additional incentive provided by the substantial fare advantage that they offer to the passenger.

Therefore the expansion growth of each of the markets analysed in the two case studies will be in great part ensured by the traffic carried by LCCs. On the other side the traffic carried by the Legacy, the Network and the Charter carriers is driven by organic growth (mainly income level), meaning that all of them are mature segments.

However the differences between these carriers and the LCC ones are fading away, as a low-cost basis is a necessary tool in the current airlines´ survival kit, taking into account their very low net operating margin, compared to other stakeholders of the air transport value chain, such as the aircraft manufacturers. The way traditional carriers are making business is more and more in line with the LCC business model, as they are trying to increase their ancillary revenues. For instance on the short and medium haul, the passenger needs to purchase the meals, because they are no more part of the purchased ticket.

In parallel, the LCCs are facing an increase of their costs as they are extending their network range and adding some frills. For these reasons, the forecast for each segment will tend to be rather the same in the next decade.

For the third case study analyzing the EU-US air travel market, it was not possible to test the confidence index through the supply side segmentation, as there was no reliable data for the Charter traffic, while the LCC traffic is non relevant as per today. Indeed, the second stage of the Air Transport Agreement has been signed very recently between EU and US, and it will take some time to witness a significant development of a new airline business model on this segment. The long-haul business model for LCCs is not yet fully successful (cf failure of Air Asia X on the Asia-Europe market) and there are still some adjustments to find before being operational on the North Atlantic.

Although consumer confidence indexes have been found useful enough in some specific time-span are significant using latest available data, for in-sample forecasts, there is no clear evidence that the use of such indexes could improve short-term traffic forecasts significantly.

According to the results obtained for this third case study, confidence appears to be useful to improve slightly the existing models, without giving an appropriate goodness of fit, as it was witnessed for the first and the second case studies.

Once again, this finding could be related to the maturity of this market which is still at the first phase of the maturity stage due to the major change which is expected to be brought by the implementation of the Air Transport Agreement.

8.2. Contribution to knowledge

While this piece of work clearly has its failings, partly due to making conclusions based on a small data samples, it does provide an initial basis to start more sophisticated analyses.

As this is the first research which has tried to formally quantify the explanatory power of the Consumer Confidence Index in air travel demand modelling, It could help in making significant progresses for the future literature that will be developed on this topic,

The results that have been presented and discussed should be of keen interest to any industry stakeholder wishing to measure the short-term impact of some events on the traffic growth.

It could notably allow through the operating concept of CCI to elaborate different scenarios of growth for decision making process, based on different assumptions linked to the CCI evolution.

These results could be for instance applied to any risk assessment exercise that needs to be made by an aircraft manufacturer when translating long-term traffic forecasts into short-term aircraft delivery planning.

Although there is no real methodological advance in the analysis of the three case studies, the models that have been built for each supply side could serve as baselines to help analysts get started with their own modeling reports, while they could be subsequently refined for specific applications.

However, there is a need to recognize that the results found are not definitive as they are highly linked both to the quality of the data used as well as to the quality of the forecasting models retained.

8.3. Limitations of the research

In this thesis, the choice has been made to use only OLS models and it is obviously possible to build other forecasting models than those that have been chosen.

It could be argued that using more sophisticated forecasting techniques could show different results, stressing for instance that consumer confidence indexes do indeed have marginal significant explanatory power, if any such methods can be found.

The main limitations to the results found are linked to the small sample size of data that were available in each market analyzed, due to the initial objective which was to analyze confidence through the supply side segmentation.

Besides, the multi-collinearity issue that has arised in some models is questioning the validity of the results, although it has been made clear through the literature review that for forecasting purposes, multi-collinearity can be accepted. Indeed the intent was not to quantify the weight of confidence as regressor but only to produce more accurate forecasts on the short-term.

It was reasonable to accept the assumption of having the same relationship in the future between the dependent and the independent variables, as the forecasts were intended for the immediate future.

Finally it is worth mentioning that while this thesis has focused on the benefits of using the CCI in a forecasting equation, the main issue stands in finding a suitable methodology for accurately forecasting consumer confidence indices. This would appear to be of prime interest for a further research study.

8.4. Suggestions for areas of future research

In the methodology used, only linear regression models were applied, and It may happen that using different forecasting methods could show the consumer confidence index with a different explanatory power.

For instance, as the indexes are released monthly, the monthly data could be used to help predict current quarter air travel demand growth. Testing this hypothesis will require the use of quite different methods and models, and will need data that are not available easily and still with a certain lag, due to the delay in releasing publicly traffic data.

This analysis could be easily done for the traffic registered by the US airlines or by the AEA airlines.

For international markets, as the business models of the airlines are becoming very close to each other, competition could be introduced in the equation modelling (for a specific international air traffic market) by using the Hirschman-Herfindahl Index so as to throw more light on the impact of alliances on market concentration by route.

Other possible steps could include the use of different forecasting techniques for comparison purposes by using the results in terms of MAPE or RMSE, in order to identify the best way to analyze the forecasting power of the confidence indices.

Another potential area of research could be to explore how consumer confidence could improve the cargo traffic forecasts, as for instance, in its Monthly monitoring report of August 2012[43], IATA is mentioning ´´…A decline in consumer confidence in major economies over recent months has weakened demand for air freighted consumer goods.´´

The consumer confidence impact is tightly linked to the travel demand for leisure purpose. Similarly, in the cases of business persons or firms, both are more willing to spend on their business activities depending on their views of a country's likely future economic course. In the international tourism literature, Swarbrooke and Horner (2001) argued that the level of economic development and state of the economy can influence the demand for business travel and tourism. Accordingly, a high level of economic development and a strong economy increase demand and vice versa. Similarly, Njegovan (2005) asserted that business expectations can be one of the leading indicators that influence the demand for business air travel. The underlying reason is that firms are more likely to authorize travel for conference and business purposes when they feel more confident about the business environment.

In conclusion, while the consumer expectations could affect households' demand for vacations, the level of business confidence could influence individual firms' demand for business travel, and this could be another potential area of research.

[43] www.**iata**.org/whatwedo/Documents/.../MIS_Note_Aug12.pdf

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Appendices

Appendix A

Percentage distribution of revenues and expenses for scheduled airlines of ICAO Member States (1993 – 2007)

DESCRIPTION	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
REVENUES															
1 Scheduled services (total)...	85.8%	86.9%	87.5%	87.4%	87.3%	87.3%	86.4%	86.7%	87.0%	86.9%	86.8%	86.7%	87.1%	87.3%	87.4%
1.1 Passenger...	75.4%	75.8%	76.4%	76.3%	75.9%	76.2%	75.5%	75.5%	75.4%	75.1%	75.0%	75.2%	76.1%	76.5%	76.4%
1.2 Excess baggage...	0.4%	0.4%	0.4%	0.4%	0.4%	0.3%	0.3%	0.3%	0.2%	0.4%	0.3%	0.3%	0.4%	0.3%	0.3%
1.3 Freight, express and diplomatic bags..........................	9.0%	9.8%	9.7%	9.9%	10.2%	10.0%	10.0%	10.3%	10.7%	10.7%	10.8%	10.6%	10.2%	10.0%	10.3%
1.4 Mail..	1.0%	0.9%	1.0%	0.9%	0.9%	0.8%	0.7%	0.7%	0.7%	0.7%	0.7%	0.6%	0.5%	0.5%	0.4%
2 Non-scheduled flights (total)..	3.6%	3.7%	4.0%	4.2%	3.9%	3.3%	3.7%	3.6%	3.4%	3.2%	3.1%	3.1%	2.5%	2.6%	2.4%
2.1 Passenger and excess baggage................................	2.8%	2.7%	3.1%	3.1%	2.8%	1.9%	2.1%	2.3%	2.3%	2.2%	2.1%	2.0%	1.6%	1.7%	1.6%
2.2 Freight (including express and diplomatic bags) and mai	0.8%	1.0%	0.9%	1.0%	1.0%	1.3%	1.7%	1.3%	1.1%	1.0%	1.0%	1.1%	0.9%	0.9%	0.8%
3 Incidental revenues (total)...	10.5%	9.4%	8.5%	8.4%	8.8%	9.5%	9.8%	9.7%	9.6%	9.9%	10.1%	10.2%	10.3%	10.1%	10.2%
4 TOTAL OPERATING REVENUES....................................	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
EXPENSES															
5 Flight operations (total)..	26.5%	25.9%	26.3%	27.7%	27.8%	26.9%	28.0%	31.1%	30.4%	30.8%	31.8%	34.5%	38.0%	39.1%	39.9%
5.1 Flight crew salaries and expenses..............................	7.4%	7.5%	7.7%	7.8%	7.8%	8.0%	8.3%	8.3%	8.7%	9.0%	9.2%	8.5%	7.8%	7.6%	7.4%
5.2 Aircraft fuel and oil..........................	**12.0%**	**11.4%**	**11.4%**	**12.8%**	**12.6%**	**10.4%**	**11.0%**	**14.4%**	**13.5%**	**13.0%**	**13.6%**	**17.3%**	**22.2%**	**23.8%**	**25.4%**
5.3 Flight equipment insurance and uninsured losses..........	0.4%	0.5%	0.5%	0.4%	0.4%	0.3%	0.2%	0.2%	0.3%	0.5%	0.4%	0.4%	0.2%	0.3%	0.2%
5.4 Rental of flight equipment...	5.6%	5.3%	5.6%	5.7%	6.0%	6.9%	7.5%	7.2%	6.9%	7.0%	7.4%	7.4%	7.0%	6.7%	6.3%
5.5 Flight crew training (when not amortized).....................	0.5%	0.4%	0.4%	0.3%	0.3%	0.3%	0.3%	0.2%	0.2%	0.2%	0.1%	0.1%	0.1%	0.1%	0.1%
5.6 Other flight expenses...	0.6%	0.7%	0.6%	0.7%	0.8%	1.0%	0.7%	0.7%	0.8%	1.1%	1.1%	0.8%	0.7%	0.7%	0.5%
6 Maintenance and overhaul..	10.1%	10.0%	10.6%	10.6%	11.0%	11.2%	10.8%	10.6%	11.3%	11.3%	10.8%	10.5%	10.2%	10.0%	10.3%
7 Depreciation and amortization (total).................................	7.0%	7.6%	7.3%	7.1%	6.5%	6.5%	6.6%	6.5%	7.1%	7.1%	6.6%	6.3%	6.1%	5.9%	6.0%
7.1 Normal depreciation of flight equipment........................	5.0%	5.6%	5.5%	5.5%	5.2%	5.0%	4.8%	5.1%	5.2%	5.5%	5.2%	4.9%	4.8%	4.7%	4.8%
7.2 Normal depreciation of ground property and equipment..	1.6%	1.5%	1.4%	1.2%	1.1%	1.2%	1.3%	1.2%	1.6%	1.3%	1.1%	1.0%	1.0%	0.9%	0.9%
7.3 Extra depreciation (in excess of cost)..........................	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
7.4 Amortization of development and pre-operating costs.....	0.3%	0.3%	0.3%	0.3%	0.2%	0.2%	0.4%	0.3%	0.3%	0.3%	0.3%	0.4%	0.3%	0.3%	0.3%
7.5 Flight crew training (when amortized)..........................	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
8 User charges and station expenses (total).........................	17.3%	17.6%	18.2%	17.7%	17.4%	17.9%	17.7%	17.2%	16.9%	17.0%	17.0%	16.5%	16.2%	16.2%	16.2%
8.1 Landing and associated airport charges.......................	4.1%	4.4%	4.5%	4.3%	4.1%	4.4%	4.4%	4.2%	4.0%	4.0%	4.0%	3.9%	3.8%	4.1%	4.1%
8.2 Route facility charges..	2.4%	2.6%	2.8%	2.7%	2.8%	3.0%	2.9%	2.8%	2.5%	2.4%	2.4%	2.5%	2.4%	2.4%	2.5%
8.3 Station expenses...	10.8%	10.5%	10.9%	10.8%	10.5%	10.4%	10.4%	10.2%	10.4%	10.6%	10.6%	10.1%	10.0%	9.7%	9.6%
9 Passenger services...	10.5%	10.8%	11.1%	10.8%	10.7%	10.6%	10.8%	10.0%	10.2%	10.2%	10.0%	9.7%	9.3%	8.9%	8.7%
10 Ticketing, sales and promotion..	16.4%	15.8%	15.6%	15.3%	14.8%	14.3%	13.7%	12.7%	11.2%	10.7%	10.0%	9.7%	9.1%	8.8%	8.5%
11 General and administrative...	7.1%	6.4%	6.2%	6.1%	6.6%	6.5%	6.1%	6.2%	7.2%	7.0%	7.1%	6.8%	5.9%	5.7%	5.3%
12 Other operating expenses..	5.2%	6.0%	4.8%	4.8%	5.2%	6.1%	6.4%	5.6%	5.7%	5.9%	6.7%	6.0%	5.2%	5.4%	5.1%
13 TOTAL OPERATING EXPENSES.....................................	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
14 OPERATING RESULT as Per Cent of Operating Revenues..	1.0%	3.1%	5.1%	4.4%	5.6%	5.4%	4.0%	3.3%	-3.8%	-1.6%	-0.5%	0.9%	1.0%	3.2%	3.9%
23 PROFIT OR LOSS (-) AFTER INCOME TAXES															
as Per Cent of Operating Revenues..................................	-1.9%	-0.1%	1.7%	1.9%	2.9%	2.8%	2.8%	1.1%	-4.2%	-3.7%	-2.3%	-1.5%	-1.0%	1.1%	2.9%

Source: ICAODATA.com (global downloads)

Appendix B

Calculation method of the US Index of Consumer Sentiment (CSI or ICS)

INDEX CALCULATIONS

Index of Consumer Sentiment

To calculate the Index of Consumer Sentiment (ICS), first compute the relative scores (the percent giving favorable replies minus the percent giving unfavorable replies, plus 100) for each of the five index questions (see x1 ...x5 listed below). Round each relative score to the nearest whole number. Using the formula shown below, sum the five relative scores, divide by the 1966 base period total of 6.7558, and add 2.0 (a constant to correct for sample design changes from the 1950s).

Index of Consumer Expectations and the Index of Current Economic Conditions

Using the same procedures given above, the Index of Current Economic Conditions (ICC) and the Index of Consumer Expectations (ICE) are calculated as follows.

Index Questions

The Index of Consumer Sentiment (ICS) is derived from the following five questions:
x1 = "We are interested in how people are getting along financially these days. Would you say that you (and your family living there) are better off or worse off financially than you were a year ago?"

x2 = "Now looking ahead--do you think that a year from now you (and your family living there) will be better off financially, or worse off, or just about the same as now?"

x3 = "Now turning to business conditions in the country as a whole--do you think that during the next twelve months we'll have good times financially, or bad times, or what?"

x4 = "Looking ahead, which would you say is more likely--that in the country as a whole we'll have continuous good times during the next five years or so, or that we will have periods of widespread unemployment or depression, or what?"

x5 = "About the big things people buy for their homes--such as furniture, a refrigerator, stove, television, and things like that. Generally speaking, do you think now is a good or bad time for people to buy major household items?"

2.0 + 6.7558 X + X + X + X + X = ICS 5 4 3 2 1 2.0 + 4.1134
X + X + X = ICE 2.0 + 2.6424
X + X = ICC 4 3 2 5 1

Appendix C

The US Consumer Confidence Index (CCI)

Methodology

The Consumer Confidence survey is conducted for The Conference Board by TNS NFO, one of TNS group of companies.

Data are available bi-monthly from 1967 through mid-1977. Beginning June 1977, data are available monthly. The questions asked to compute the indexes have remained constant throughout the history of the series. The Index is based on responses to 5 questions included in the survey:

1. Respondents appraisal of current business conditions.
2. Respondents expectations regarding business conditions six months hence.
3. Respondents appraisal of the current employment conditions.
4. Respondents expectations regarding employment conditions six months hence.
5. Respondents expectations regarding their total family income six months hence.

For each of the 5 questions, there are three response options: POSITIVE, NEGATIVE and NEUTRAL.

The response proportions to each question are seasonally adjusted. For each of the five question (above), the POSITIVE figure is divided by the sum of the POSITIVE and NEGATIVE to yield a proportion, which we call the "RELATIVE" value. For each question, the average RELATIVE for the calendar year 1985 is then used as a benchmark to yield the INDEX value for that question. The Indexes are then averaged together as follows: Consumer Confidence Index: Average of all 5 Indexes; Present Situation Index: Average of indexes for questions 1 and 3; Expectations Index: Average of Indexes for questions 2, 4, and 5.

Appendix D

Domestic US: ADF tests for RPMs and CSI Current

Table D1: ADF test on ´´D(log(adjusted RPM))´´ (1st difference)

Null Hypothesis: D(LRPM) has a unit root
Exogenous: None
Lag Length: 1 (Automatic based on SIC, MAXLAG=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-13.44684	0.0000
Test critical values:	1% level	-2.578092	
	5% level	-1.942634	
	10% level	-1.615508	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LRPM,2)
Method: Least Squares
Date: 02/02/00 Time: 17:56
Sample (adjusted): 1996M04 2010M12
Included observations: 177 after adjustments

	Coefficient	Std. Error	t-Statistic	Prob.
D(LRPM(-1))	-1.646541	0.122448	-13.44684	0.0000
D(LRPM(-1),2)	0.200801	0.073546	2.730287	0.0070

R-squared	0.698359	Mean dependent var	6.56E-05
Adjusted R-squared	0.696635	S.D. dependent var	0.063800
S.E. of regression	0.035140	Akaike info criterion	-3.847705
Sum squared resid	0.216096	Schwarz criterion	-3.811816
Log likelihood	342.5219	Hannan-Quinn criter.	-3.833150
Durbin-Watson stat	2.046738		

Table D2: ADF test on ´´D(log CSI Current (I2C))´´ (1st difference)

Null Hypothesis: D(LI2C) has a unit root
Exogenous: None
Lag Length: 1 (Automatic based on SIC, MAXLAG=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-12.54270	0.0000
Test critical values:	1% level	-2.578092	
	5% level	-1.942634	
	10% level	-1.615508	

*MacKinnon (1996) one-sided p-values.

Sample (adjusted): 1996M04 2010M12
Included observations: 177 after adjustments

	Coefficient	Std. Error	t-Statistic	Prob.
D(LI2C(-1))	-1.491053	0.118878	-12.54270	0.0000
D(LI2C(-1),2)	0.186850	0.075006	2.491121	0.0137

R-squared	0.639585	Mean dependent var	0.000205
Adjusted R-squared	0.637525	S.D. dependent var	0.077927
S.E. of regression	0.046916	Akaike info criterion	-3.269660
Sum squared resid	0.385202	Schwarz criterion	-3.233771
Log likelihood	291.3649	Hannan-Quinn criter.	-3.255105
Durbin-Watson stat	2.017425		

Appendix E

Domestic US: Co-integration and Granger tests for RPMs and CSI Current

Table E1: Co-integration test for log (RPM) and log (I2C)

Included observations: 175 after adjustments
Trend assumption: Linear deterministic trend
Series: LRPM LI2C
Lags interval (in first differences): 1 to 4

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None	0.042193	10.14509	15.49471	0.2697
At most 1	0.014753	2.600996	3.841466	0.1068

Trace test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None	0.042193	7.544097	14.26460	0.4269
At most 1	0.014753	2.600996	3.841466	0.1068

Max-eigenvalue test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Table E2: Granger Causality Test for lag 5 and 13

Pairwise Granger Causality Tests
Date: 02/02/00 Time: 18:01
Sample: 1996M01 2010M12
Lags: 5

Null Hypothesis:	Obs	F-Statistic	Prob.
LI2C does not Granger Cause LRPM	175	0.99583	0.4221
LRPM does not Granger Cause LI2C		1.91776	0.0940

Pairwise Granger Causality Tests
Date: 02/02/00 Time: 18:02
Sample: 1996M01 2010M12
Lags: 13

Null Hypothesis:	Obs	F-Statistic	Prob.
LI2C does not Granger Cause LRPM	167	1.69328	0.0685
LRPM does not Granger Cause LI2C		0.87905	0.5765

Appendix F

Domestic US: Identification of the lag length impact

Table F1: Lag length impact on RPM

Vector Autoregression Estimates
Date: 02/02/00 Time: 18:05
Sample (adjusted): 1997M02 2010M12
Included observations: 167 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	LRPM	LI2C
LRPM(-1)	0.471413 (0.08521) [5.53240]	0.071127 (0.11575) [0.61451]
LRPM(-2)	0.135193 (0.09319) [1.45076]	-0.016893 (0.12658) [-0.13345]
LRPM(-3)	0.118531 (0.09213) [1.28656]	-0.173786 (0.12515) [-1.38864]
LRPM(-4)	0.081639 (0.09274) [0.88026]	0.073502 (0.12598) [0.58344]
LRPM(-5)	-0.012606 (0.09313) [-0.13537]	-0.106579 (0.12650) [-0.84252]
LRPM(-6)	0.023104 (0.09319) [0.24792]	0.010016 (0.12659) [0.07912]
LRPM(-7)	0.086405 (0.09276) [0.93146]	0.010067 (0.12601) [0.07989]
LRPM(-8)	-0.014271 (0.09289) [-0.15363]	-0.102952 (0.12618) [-0.81589]
LRPM(-9)	0.063928 (0.09242) [0.69172]	0.080637 (0.12554) [0.64232]
LRPM(-10)	-0.045201 (0.09191)	-0.027607 (0.12485)
LRPM(-11)	0.006976 (0.09229) [0.07559]	0.077033 (0.12536) [0.61449]
LRPM(-12)	0.074198 (0.09084) [0.81681]	-0.078848 (0.12339) [-0.63900]
LRPM(-13)	-0.004338 (0.08229) [-0.05272]	0.092888 (0.11179) [0.83095]
LI2C(-1)	0.043107 (0.06225) [0.69245]	0.634886 (0.08456) [7.50791]
LI2C(-2)	-0.065596 (0.07342) [-0.89343]	0.065708 (0.09973) [0.65884]
LI2C(-3)	0.102778 (0.07423) [1.38462]	0.127069 (0.10083) [1.26024]
LI2C(-4)	-0.058781 (0.07409) [-0.79337]	0.132976 (0.10064) [1.32128]
LI2C(-5)	0.165402 (0.07374) [2.24305]	0.053573 (0.10017) [0.53484]
LI2C(-6)	-0.043642 (0.07542) [-0.57864]	0.139474 (0.10245) [1.36137]
LI2C(-7)	0.052833 (0.07674) [0.68849]	-0.096388 (0.10424) [-0.92470]
LI2C(-8)	-0.043064 (0.07670) [-0.56146]	-0.032662 (0.10419) [-0.31349]
LI2C(-9)	0.046178 (0.07619)	0.117351 (0.10349)
LI2C(-10)	-0.140428 (0.07566) [-1.85601]	-0.192949 (0.10278) [-1.87737]
LI2C(-11)	-0.067807 (0.07643) [-0.88713]	0.086568 (0.10383) [0.83377]
LI2C(-12)	0.024998 (0.07698) [0.32473]	0.057770 (0.10457) [0.55244]
LI2C(-13)	-0.006949 (0.06574) [-0.10570]	-0.157099 (0.08930) [-1.75929]
C	0.229255 (0.59091) [0.38797]	1.898292 (0.80268) [2.36494]
R-squared	0.909157	0.933296
Adj. R-squared	0.892286	0.920908
Sum sq. resids	0.169953	0.313596
S.E. equation	0.034842	0.047328
F-statistic	53.88943	75.33924
Log likelihood	338.3711	287.2205
Akaike AIC	-3.728995	-3.116413
Schwarz SC	-3.224888	-2.612306
Mean dependent	17.57809	4.587419
S.D. dependent	0.106161	0.168289

Determinant resid covariance (dof adj.)	2.67E-06
Determinant resid covariance	1.88E-06
Log likelihood	626.9815
Akaike information criterion	-6.862054
Schwarz criterion	-5.853840

Table F2: Log RPM model with Lag values of CSI Current

Dependent Variable: LRPM
Method: Least Squares
Date: 02/02/00 Time: 18:07
Sample (adjusted): 1996M06 2010M12
Included observations: 175 after adjustments

	Coefficient	Std. Error	t-Statistic	Prob.
C	18.60280	0.231785	80.25888	0.0000
LI2C(-3)	-0.242594	0.136475	-1.777575	0.0772
LI2C(-5)	0.017634	0.137921	0.127855	0.8984

R-squared	0.109427	Mean dependent var	17.56906
Adjusted R-squared	0.099071	S.D. dependent var	0.111805
S.E. of regression	0.106122	Akaike info criterion	-1.631453
Sum squared resid	1.937057	Schwarz criterion	-1.577200
Log likelihood	145.7522	Hannan-Quinn criter.	-1.609447
F-statistic	10.56701	Durbin-Watson stat	0.157421
Prob(F-statistic)	0.000047		

Appendix G

Domestic US: ADF tests for the quarterly time series from 1996 to 2010

Table G1: ADF test for the RPM quarterly series

Null Hypothesis: D(LRPM) has a unit root
Exogenous: None
Lag Length: 3 (Automatic based on SIC, MAXLAG=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.605927	0.0005
Test critical values:	1% level	-2.607686	
	5% level	-1.946878	
	10% level	-1.612999	

*MacKinnon (1996) one-sided p-values.

Table G2: ADF test for the GDP quarterly series

Null Hypothesis: D(LGDPR) has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic based on SIC, MAXLAG=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.109231	0.0314
Test critical values:	1% level	-3.550396	
	5% level	-2.913549	
	10% level	-2.594521	

*MacKinnon (1996) one-sided p-values.

Appendix H

Domestic US: Statistical tests for Model 1

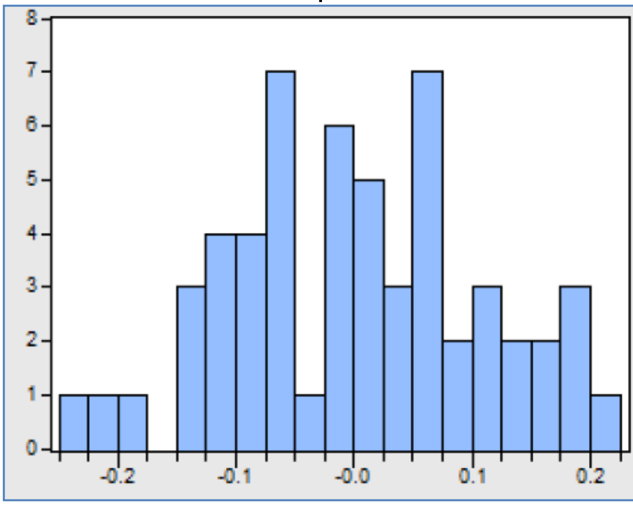
Table H1: Normality of residuals

Sample (adjusted): 1996Q2 2010Q4
Included observations: 59 after adjustments

	Coefficient	Std. Error	t-Statistic	Prob.
C	10.63477	0.987858	10.76549	0.0000
LGDPR(-1)	0.749351	0.106700	7.022961	0.0000

R-squared	0.463893	Mean dependent var	17.57175
Adjusted R-squared	0.454487	S.D. dependent var	0.146484
S.E. of regression	0.108192	Akaike info criterion	-1.576517
Sum squared resid	0.667208	Schwarz criterion	-1.506092
Log likelihood	48.50724	Hannan-Quinn criter.	-1.549025
F-statistic	49.32199	Durbin-Watson stat	1.647686
Prob(F-statistic)	0.000000		

Table H2: Jarque-Bera test for normality of residuals



Series: Residuals
Sample 1996Q1 2009Q4
Observations 56

Mean	1.87e-15
Median	-0.000942
Maximum	0.205941
Minimum	-0.233369
Std. Dev.	0.107319
Skewness	0.020054
Kurtosis	2.302126
Jarque-Bera	1.140153
Probability	0.565482

Table H3: White´s test

Heteroskedasticity Test: White

F-statistic	0.225969	Prob. F(2,53)	0.7985
Obs*R-squared	0.473482	Prob. Chi-Square(2)	0.7892
Scaled explained SS	0.286641	Prob. Chi-Square(2)	0.8665

<u>Appendix I</u>

Domestic US: Statistical tests for Model 2

Table I1: Inferences tests for Model 2

Sample (adjusted): 1996Q2 2010Q4
Included observations: 59 after adjustments

	Coefficient	Std. Error	t-Statistic	Prob.
C	5.712630	1.690667	3.378921	0.0013
LGDPR(-1)	1.085163	0.138023	7.862214	0.0000
LI2C(-1)	0.394514	0.114448	3.447088	0.0011

R-squared	0.557735	Mean dependent var	17.57175
Adjusted R-squared	0.541940	S.D. dependent var	0.146484
S.E. of regression	0.099141	Akaike info criterion	-1.735044
Sum squared resid	0.550418	Schwarz criterion	-1.629406
Log likelihood	54.18378	Hannan-Quinn criter.	-1.693807
F-statistic	35.31047	Durbin-Watson stat	1.906112
Prob(F-statistic)	0.000000		

Table I2: Test for normality of residuals for Model 2

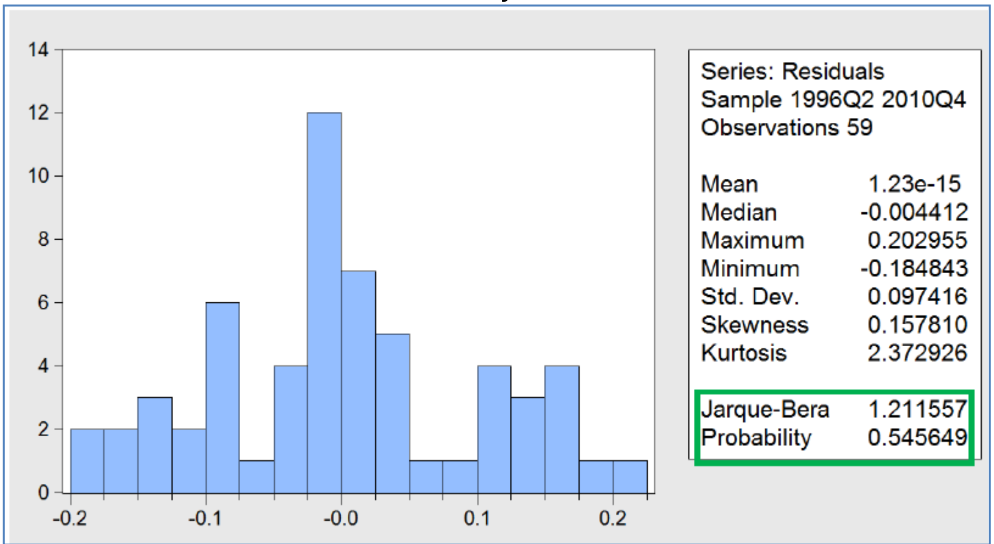


Table I3: White´s test for Model 2

Heteroskedasticity Test: White

F-statistic	0.943494	Prob. F(5,53)	0.4607
Obs*R-squared	4.822295	Prob. Chi-Square(5)	0.4380
Scaled explained SS	2.982243	Prob. Chi-Square(5)	0.7027

Appendix J

Domestic US: Normal distribution tests for the variable Log RPK 85-2010

Table J1:Statistical measures for Log RPK 85-2010

Basic Statistical Measure for Log RPK 85-2010s			
Location		Variability	
Mean	13.44617	Std Deviation	0.24145
Median	13.49031	Variance	0.05830
Mode	.	Range	0.80335
		Interquartile Range	0.47854

Basic Confidence Limits Assuming Normality			
Parameter	Estimate	95% Confidence Limits	
Mean	13.44617	13.34865	13.54370
Std Deviation	0.24145	0.18936	0.33331
Variance	0.05830	0.03586	0.11109

Table J2:Normality measures for Log RPK 85-2010

Tests for Location: Mu0=0				
Test		Statistic	p Value	
Student's t	t	283.9551	Pr > |t|	<.0001
Sign	M	13	Pr >= |M|	<.0001
Signed Rank	S	175.5	Pr >= |S|	<.0001

Tests for Normality				
Test		Statistic	p Value	
Shapiro-Wilk	W	0.931517	Pr < W	0.0842
Kolmogorov-Smirnov	D	0.13411	Pr > D	>0.1500
Cramer-von Mises	W-Sq	0.100563	Pr > W-Sq	0.1058
Anderson-Darling	A-Sq	0.639328	Pr > A-Sq	0.0881

Parameters for Normal Distribution		
Parameter	Symbol	Estimate
Mean	Mu	13.44617
Std Dev	Sigma	0.241455

Quantiles for Normal Distribution		
	Quantile	
Percent	Observed	Estimated
1.0	12.9840	12.8845
5.0	13.0941	13.0490
10.0	13.1661	13.1367
25.0	13.2130	13.2833
50.0	13.4903	13.4462
75.0	13.6915	13.6090
90.0	13.7468	13.7556
95.0	13.7556	13.8433
99.0	13.7873	14.0079

Appendix K

Domestic US: Statistical tables for Model 1 of Log RPK 85-2010

Table K1: Model 1 specifications for Log (RPK 1985-2010)

Model 1 Variable: Log RPK 85-2010	Parameter Estimate	Standard Error	Type II SS	F Value	Pr > F
Intercept	3.49779	0.28915	0.1765	146.33	<.0001
Log RGDP	1.0809	0.03141	1.42856	1184.41	<.0001
Root MSE	0.03473	R-Square	0.9801		
Dependent Mean	13.44617	Adj R-Sq	0.9793		
Coeff Var	0.25828				

Table K2: Residuals and Predictions for Model 1 of Log (RPK 1985-2010)

Year	Log RPK	predicted_Log RPK	residual_Log RPK
1985	12.98	13.0442	-0.060279
1986	13.09	13.081	0.013048
1987	13.17	13.1151	0.050991
1988	13.18	13.1586	0.021736
1989	13.18	13.1966	-0.014188
1990	13.21	13.2167	-0.003678
1991	13.19	13.2141	-0.023932
1992	13.24	13.2502	-0.014832
1993	13.25	13.2806	-0.027439
1994	13.32	13.3238	-0.002886
1995	13.36	13.3506	0.009627
1996	13.44	13.3903	0.046341
1997	13.48	13.4374	0.039382
1998	13.5	13.4835	0.020282
1999	13.56	13.5345	0.022837
2000	13.61	13.5783	0.036017
2001	13.56	13.5899	-0.032023
2002	13.54	13.6093	-0.073136
2003	13.6	13.6359	-0.037333
2004	13.7	13.6739	0.022932
2005	13.75	13.7064	0.039471
2006	13.76	13.7349	0.02074
2007	13.79	13.7557	0.031551
2008	13.75	13.7557	-0.00897
2009	13.69	13.7269	-0.035379
2010	13.72	13.7562	-0.04088

Appendix L

Domestic US: Comparison of the stepwise results for Model 1 and 2 of Log RPK 85-2010

Table L1: Significance tests for Model 1 of Log (RPK 85-2010)

Model 1: Summary of Stepwise Selection Dependent Variable: Log RPK 85-2010

Step	Variable Entered	Variable Removed	Number Vars In	Partial R-Square	Model R-Square	C(p)	F Value	Pr > F
1	Log RGDP		1	0.9801	0.9801	3.2158	1184.41	<.0001

Model 1: Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	1.42856	1.42856	1184.41	<.0001
Error	24	0.02895	0.00121		
Corrected Total	25	1.45751			

Root MSE	0.03473	R-Square	0.9801
Dependent Mean	13.44617	Adj R-Sq	0.9793
Coeff Var	0.25828		

Table L2: Significance tests for Model 2 of Log (RPK 85-2010)

Model 2: Summary of Stepwise Selection Dependent Variable: Log RPK85-2010

Step	Variable Entered	Variable Removed	Number Vars In	Partial R-Square	Model R-Square	C(p)	F Value	Pr > F
1	Log RGDP		1	0.9801	0.9801	9.9619	1184.41	<.0001
2	LnCSI Curr		2	0.0063	0.9865	1.7754	10.76	0.0033

Model 2: Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	2	1.43779	0.71889	838.40	<.0001
Error	23	0.01972	0.00085746		
Corrected Total	25	1.45751			

Root MSE	0.02928	R-Square	0.9865
Dependent Mean	13.44617	Adj R-Sq	0.9853
Coeff Var	0.21777		

Appendix M

Domestic US: Comparison of statistical results for Model 1 and 2 of Log RPK 85-2010

Table M1: Additional tests for Model 1 of Log (RPK 85-2010)

Number in Model 1	C(p)	R-Square	Adjusted R-Square	AIC	BIC	MSE	Prediction Criterion	Root MSE	SBC	SSE	Variables in Model
1	2.0000	0.9801	0.9793	-172.8098	-170.4904	0.00121	0.0232	0.03473	-170.29366	0.02895	Log RGDP

Table M2: Additional tests for Model 2 of Log (RPK 85-2010)

Number in Model 2	C(p)	R-Square	Adjusted R-Square	AIC	BIC	MSE	Prediction Criterion	Root MSE	SBC	SSE	Variables in Model
2	3.0000	0.9865	0.9853	-180.7877	-178.0392	0.00085746	0.0171	0.02928	-177.01345	0.01972	Log RGDP LnCSI Curr
1	11.7594	0.9801	0.9793	-172.8098	-171.8349	0.00121	0.0232	0.03473	-170.29366	0.02895	Log RGDP
1	1582.278	0.0562	0.0169	-72.4194	-76.2903	0.05732	1.1011	0.23941	-69.90324	1.37560	LnCSI Curr

Table M3: Parameter estimates for Model 1 and 2 of Log (RPK 85-2010)

Variable	DF	MODEL 1 Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	3.49779	0.28915	12.1	<.0001
Log RGDP	1	1.0809	0.03141	34.42	<.0001

Variable	DF	MODEL 2 Parameter Estimate	Standard Error	t Value	Pr > |t
Intercept	1	2.50313	0.38909	6.43	<.0001
Log RGDP	1	1.10981	0.02791	39.77	<.0001
LnCSI Curr	1	0.15828	0.04825	3.28	0.0033

Appendix N

Domestic US: Statistical results for Model 3 of Log RPK 85-2010

Table N1: Specifications of Model 3 for Log (RPK 85-2010)

Model 3: Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	2	1.43663	0.71831	791.26	<.0001
Error	23	0.02088	0.00090781		
Corrected Total	25	1.45751			

Root MSE	0.03013	R-Square	0.9857
Dependent Mean	13.44617	Adj R-Sq	0.9844
Coeff Var	0.22408		

Number in Model 3	C(p)	R-Square	Adjusted R-Square	AIC	BIC	MSE	Prediction Criterion	Root MSE	SBC	SSE	Variables in Model
2	3.0000	0.9857	0.9844	-179.3039	-176.5553	0.00090781	0.0181	0.03013	-175.52960	0.02088	Log RGDP Dummy
1	9.8867	0.9801	0.9793	-172.8098	-171.6165	0.00121	0.0232	0.03473	-170.29366	0.02895	Log RGDP
1	1517.560	0.0411	0.0011	-72.0062	-75.8717	0.05823	1.1187	0.24132	-69.49000	1.39763	Dummy

Table N2: Parameters of Model 3 for Log (RPK 85-2010)

Variable: Log RPK 85-2010	DF	MODEL 3 Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	3.91746	0.57132	6.86	<.0001
Log RGDP	1	1.03783	0.06121	16.96	<.0001
Dummy	1	-0.05161	0.01716	-3.01	0.0101

Appendix O

Domestic US: Comparison of statistical results for Model 1 and 2 of Log (RPK 85-2000)

Table O1: Specifications of Model 1for Log (RPK 85-2000)

Model 1 Variable: Log RPK 1985-2000	Parameter Estimate	Standard Error	Type II SS	F Value	Pr > F
Intercept	2.39628	0.42882	0.02245	31.23	<.0001
LnRGDP 85-2000	1.22580	0.04821	0.46476	646.48	<.0001
Root MSE		0.02681	R-Square		0.9788
Dependent Mean		13.29804	**Adj R-Sq**		**0.9773**
Coeff Var		0.20163			

Table O2: Specifications of Model 2 for Log (RPK 85-2000)

Model 2 Variable: Log RPK 1985-2000	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	2.0312	0.44405	4.57	0.0005
LnRGDP 85-2000	1.17948	0.05128	23	<.0001
LnCSI Curr 85-2000	0.1671	0.09126	1.83	0.0901
Root MSE	0.02481	R-Square	0.9831	
Dependent Mean	13.29804	**Adj R-Sq**	**0.9806**	
Coeff Var	0.18656			

Appendix P

Domestic US: Comparison of statistical results for Model 1 and 2 of Log (RPK 85-2007)

Table P1: Specifications of Model 1 for Log (RPK 85-2007)

Model 1 Variable: Log RPK 1985-2007	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	3.2877	0.29481	11.15	<.0001
LnRGDP 85-2007	1.11953	0.0326	34.35	<.0001
Root MSE	0.03169	R-Square	0.9825	
Dependent Mean	13.41073	**Adj R-Sq**	**0.9817**	
Coeff Var	0.23629			

Table P2: Specifications of Model 2 for Log (RPK 85-2007)

Model 2 Variable: Log RPK 1985-2007	**Parameter Estimate**	**Standard Error**	**Type II SS**	**F Value**	**Pr > F**
Intercept	2.11771	0.39774	0.01798	28.35	<.0001
LnRGDP 85-2007	1.10523	0.02620	1.12848	1779.44	<.0001
Log CSI Curr 85-2007	0.27993	0.07690	0.00840	13.25	0.0016
Root MSE	0.02518	R-Square		0.9895	
Dependent Mean	13.41073	**Adj R-Sq**		**0.9884**	
Coeff Var	0.18778				

Appendix Q

Domestic US: Comparison of statistical results for Model 1 and 2 of Log (RPK 95-2007) for the Legacy segment

Table Q1: Model 1 and 2 for the Legacy segment between 1995 and 2007

Model 1 **Variable :** **Log RPK Leg 95-2007**	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-3.06111	1.28884	-2.38	0.0368
LogRGDPCap95_07	1	0.8982	0.12183	7.37	<.0001
		Analysis of Variance			
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	0.06314	0.06314	54.36	<.0001
Error	11	0.01278	0.00116		
Corrected Total	12	0.07591			
Root MSE	0.03408	R-Square	0.8317	.	.
Dependent Mean	6.44073	Adj R-Sq	0.8164	.	.
Coeff Var	0.52916			.	.
Model 2 **Variable:** **Log RPK Leg 95-2007**	**DF**	**Parameter**	**Standard**	**t Value**	**Pr > |t|**
		Estimate	Error		
Intercept	1	-6.76897	1.02671	-6.59	<.0001
LogRGDPCap95_07	1	1.03184	0.07281	14.17	<.0001
Log CSICurr95-07	1	0.49179	0.0974	5.05	0.0005
		Analysis of Variance			
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.07231	0.03616	100.44	<.0001
Error	10	0.0036	0.00036		
Corrected Total	12	0.07591			
Root MSE	0.01897	R-Square	0.9526		
Dependent Mean	6.44073	Adj R-Sq	0.9431		
Coeff Var	0.29459				

Appendix R

Domestic US: Comparison of statistical results for Model 1 and 2 of Log (RPK 95-2007) for the LCC segment

Table R1: Model 1 and 2 for the LCC segment between 1995 and 2007

Model 1 Variable: LogRPKLCC 95-07	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-17.05316	3.60705	-4.73	0.0004
Log RLCCYields95-07	1	-0.94757	0.35638	-2.66	0.0197
Log RDP95-07	1	2.51783	0.3324	7.57	<.0001

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	2	2.66797	1.33399	456.93	<.0001
Error	13	0.03795	0.00292		
Corrected Total	15	2.70592			

Model 2 Variable: Log RPK LCC95-07	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-15.8719	3.50151	-4.53	0.0007
Log CSICurr95-07	1	0.44509	0.28357	1.57	0.1425
Log RLCCYields95-07	1	-1.44544	0.46343	-3.12	0.0089
Log RDP95-07	1	2.24909	0.35864	6.27	<.0001

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	3	2.67444	0.89148	339.74	<.0001
Error	12	0.03149	0.00262		
Corrected Total	15	2.70592			

Appendix S

Comparison of statistical results for Model 1 and 2 of Log (RPK 95-2007) for the whole US Domestic traffic

Table S1: Model 1 and 2 for the whole US domestic traffic between 95 & 2007

Model 1 Variable: Log RPK 95-07	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	3.88751	0.83414	4.66	0.0007
Log RGDP95-07	1	1.04031	0.08946	11.63	<.0001

Analysis of Variance

Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	0.18878	0.18878	135.23	<.0001
Error	11	0.01536	0.0014		
Corrected Total	12	0.20414			
Root MSE	0.03736	R-Square	0.9248		
Dependent Mean	13.58672	**Adj R-Sq**	**0.9179**		
Coeff Var	0.275				

Model 2 Variable: Log RPK 95-07	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	0.97499	1.147	0.85	0.4152
Log RGDP95-07	1	1.12894	0.07365	15.33	<.0001
Log CSICurr95-07	1	0.44724	0.14712	3.04	0.0125

Analysis of Variance

Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**			
Model	2	0.19616	0.09808	122.9	<.0001	.	.	.
Error	10	0.00798	0.000798			.	.	.
Corrected Total	12	0.20414				.	.	.
Root MSE	0.02825	R-Square	0.9609					
Dependent Mean	13.58672	Adj R-Sq	0.9531					
Coeff Var	0.20792							

Appendix T

The joint harmonised EU consumer survey *(Source: EU Commission)*

The consumer confidence indicator is the arithmetic average of the balances (in percentage points) of the answers to the survey questions on the financial situation of households, the general economic situation, unemployment expectations (with inverted sign) and savings, all over the next 12 months. Balances are seasonally adjusted.

Consumer survey - Questionnaire
Monthly questions

Q1 How has the financial situation of your household changed over the last 12 months? It has...
+ + got a lot better
+ got a little better
= stayed the same
- got a little worse
- - got a lot worse
N don't know.

Q2 How do you expect the financial position of your household to change over the next 12 months? It will...
+ + get a lot better
+ get a little better
= stay the same
- get a little worse
- - get a lot worse
N don't know.

Q3 How do you think the general economic situation in the country has changed over the past 12 months? It has...
+ + got a lot better
+ got a little better
= stayed the same
- got a little worse
- - got a lot worse
N don't know.

Q4 How do you expect the general economic situation in this country to develop over the next 12 months? It will...
+ + get a lot better
+ get a little better
= stay the same
- get a little worse
- - get a lot worse
N don't know.

Q5 How do you think that consumer prices have developed over the last 12 months? They have…
+ + risen a lot
+ risen moderately
= risen slightly
- stayed about the same
- - fallen
N don't know.

Q6 By comparison with the past 12 months, how do you expect that consumer prices will develop in the next 12 months? They will…
+ + increase more rapidly
+ increase at the same rate
= increase at a slower rate
- stay about the same
- - fall
N don't know.

Q7 How do you expect the number of people unemployed in this country to change over the next 12 months? The number will...
+ + increase sharply
+ increase slightly
= remain the same
- fall slightly
- - fall sharply
N don't know.

Q8 In view of the general economic situation, do you think that now it is the right moment for people to make major purchases such as furniture, electrical/electronic devices, etc.?
+ + yes, it is the right moment now
= it is neither the right moment nor the wrong moment
- - no, it is not the right moment now
N don't know.

Q9 Compared to the past 12 months, do you expect to spend more or less money on major purchases
(furniture, electrical/electronic devices, etc.) over the next 12 months? I will spend…
+ + much more
+ a little more
= about the same
- a little less
- - much less
N don't know.

Q10 In view of the general economic situation, do you think that now is...?
+ + a very good moment to save
+ a fairly good moment to save
- not a good moment to save
- - a very bad moment to save
N don't know.

Q11 Over the next 12 months, how likely is it that you save any money?
+ + very likely
+ fairly likely
- not likely
- - not at all likely
N don't know.

Q12 Which of these statements best describes the current financial situation of your household?
+ + we are saving a lot
+ we are saving a little
= we are just managing to make ends meet
on our income
- we are having to draw on our savings
- - we are running into debt
N don't know.

Appendix U

EU country weights private final consumption expenditure at 2000 prices and 2000 exchange rates

***Country codes: BE**: Belgium, **BG**: Bulgaria, **CZ**: Czech Republic, **DK**: Denmark, **DE**: Germany, **EE**: Estonia, **IE**: Ireland, **EL**: Greece, **ES**: Spain, **FR**: France, **IT**: Italy, **CY**: Cyprus, **LV**: Latvia, **LT**: Lithuania, **LU**: Luxembourg, **HU**: Hungary, **MT:** Malta, **NL**: Netherlands, **AT**: Austria, **PL**: Poland, **PT**: Portugal, **RO**: Romania, **SI:** Slovenia, **SK:** Slovakia, **FI**: Finland, **SE:** Sweden, **UK:** United Kingdom*

***(2)** : Estimated value*

Source: EU Commission

	BE	BG	CZ	DK	DE	EE	IE	EL	ES	FR	IT	CY	LV	LT	LU	HU	MT	NL	AT	PL	PT	RO	SI	SK	FI	SE	UK
1985	0.027	0.002	0.006	0.018	0.233	0.001	0.007	0.017	0.064	0.162	0.140	0.001	0.001	0.001	0.001	0.005	0.000	0.039	0.023	0.017	0.012	0.007	0.002	0.002	0.013	0.027	0.171
1986	0.027	0.002	0.006	0.019	0.231	0.001	0.007	0.016	0.064	0.161	0.141	0.001	0.001	0.001	0.001	0.005	0.000	0.038	0.023	0.017	0.012	0.007	0.002	0.002	0.013	0.027	0.174
1987	0.026	0.002	0.006	0.018	0.230	0.001	0.007	0.016	0.064	0.160	0.141	0.001	0.001	0.001	0.001	0.005	0.000	0.038	0.022	0.017	0.012	0.007	0.002	0.002	0.013	0.028	0.178
1988	0.026	0.002	0.006	0.017	0.228	0.001	0.007	0.016	0.065	0.159	0.140	0.001	0.001	0.001	0.001	0.005	0.000	0.037	0.022	0.017	0.013	0.007	0.002	0.002	0.014	0.028	0.182
1989	0.026	0.002	0.006	0.017	0.226	0.001	0.007	0.016	0.066	0.158	0.141	0.001	0.001	0.001	0.001	0.005	0.000	0.036	0.022	0.017	0.013	0.007	0.002	0.002	0.014	0.027	0.185
1990	0.026	0.002	0.006	0.016	0.228	0.001	0.007	0.016	0.067	0.157	0.141	0.001	0.001	0.001	0.001	0.005	0.000	0.036	0.022	0.017	0.013	0.007	0.002	0.002	0.014	0.026	0.183
1991	0.026	0.002	0.006	0.016	0.233	0.001	0.007	0.017	0.068	0.156	0.141	0.001	0.001	0.001	0.002	0.005	0.000	0.037	0.023	0.017	0.013	0.006	0.002	0.002	0.013	0.026	0.179
1992	0.026	0.002	0.006	0.016	0.236	0.001	0.007	0.017	0.068	0.155	0.142	0.001	0.001	0.001	0.002	0.005	0.000	0.037	0.023	0.018	0.014	0.006	0.002	0.002	0.012	0.026	0.175
1993	0.026	0.002	0.006	0.016	0.239	0.001	0.007	0.017	0.068	0.154	0.140	0.001	0.001	0.001	0.002	0.005	0.000	0.037	0.023	0.018	0.014	0.005	0.002	0.002	0.012	0.025	0.177
1994	0.026	0.002	0.006	0.016	0.239	0.001	0.007	0.017	0.067	0.153	0.137	0.001	0.001	0.001	0.002	0.005	0.000	0.036	0.023	0.019	0.014	0.005	0.002	0.002	0.012	0.024	0.180
1995	0.026	0.002	0.006	0.017	0.239	0.001	0.007	0.017	0.066	0.153	0.136	0.001	0.001	0.001	0.002	0.005	0.000	0.037	0.023	0.019	0.014	0.006	0.002	0.002	0.012	0.024	0.181
1996	0.026	0.002	0.006	0.017	0.238	0.001	0.008	0.017	0.066	0.152	0.135	0.001	0.001	0.001	0.002	0.005	0.000	0.037	0.023	0.020	0.014	0.006	0.002	0.002	0.012	0.024	0.182
1997	0.026	0.002	0.006	0.017	0.236	0.001	0.008	0.017	0.067	0.150	0.135	0.001	0.001	0.001	0.002	0.005	0.000	0.038	0.023	0.021	0.014	0.006	0.002	0.002	0.012	0.024	0.185
1998	0.026	0.002	0.006	0.017	0.232	0.001	0.008	0.017	0.067	0.149	0.136	0.001	0.001	0.001	0.002	0.005	0.000	0.038	0.023	0.022	0.014	0.006	0.002	0.002	0.012	0.024	0.186
1999	0.025	0.002	0.006	0.016	0.229	0.001	0.009	0.017	0.068	0.149	0.135	0.001	0.001	0.001	0.002	0.005	0.000	0.039	0.022	0.022	0.014	0.006	0.002	0.002	0.012	0.024	0.188
2000	0.025	0.002	0.006	0.016	0.227	0.001	0.009	0.018	0.069	0.149	0.133	0.001	0.001	0.001	0.002	0.005	0.001	0.039	0.022	0.022	0.015	0.005	0.002	0.002	0.012	0.024	0.189
2001	0.025	0.002	0.006	0.015	0.225	0.001	0.009	0.018	0.070	0.150	0.132	0.001	0.001	0.002	0.002	0.005	0.001	0.039	0.022	0.022	0.014	0.005	0.002	0.002	0.012	0.024	0.191
2002	0.025	0.002	0.006	0.015	0.222	0.001	0.010	0.019	0.071	0.150	0.130	0.001	0.001	0.002	0.002	0.005	0.001	0.039	0.022	0.022	0.014	0.006	0.002	0.002	0.012	0.024	0.194
2003	0.025	0.002	0.006	0.015	0.218	0.001	0.010	0.019	0.072	0.151	0.128	0.001	0.001	0.002	0.002	0.006	0.000	0.038	0.022	0.023	0.014	0.006	0.002	0.002	0.012	0.024	0.196
2004	0.024	0.002	0.006	0.015	0.214	0.001	0.010	0.020	0.073	0.152	0.127	0.001	0.001	0.002	0.002	0.006	0.001	0.038	0.021	0.023	0.014	0.006	0.002	0.003	0.013	0.024	0.199
2005	0.024	0.002	0.006	0.015	0.210	0.001	0.010	0.020	0.075	0.152	0.125	0.001	0.001	0.002	0.002	0.006	0.001	0.037	0.021	0.023	0.014	0.007	0.002	0.003	0.013	0.025	0.200
2006	0.024	0.002	0.006	0.016	0.207	0.001	0.011	0.020	0.076	0.152	0.124	0.001	0.001	0.002	0.002	0.006	0.001	0.037	0.021	0.023	0.014	0.008	0.002	0.003	0.013	0.025	0.199
2007	0.024	0.002	0.007	0.016	0.204	0.001	0.011	0.021	0.077	0.152	0.124	0.001	0.002	0.002	0.002	0.006	0.001	0.036	0.021	0.024	0.014	0.009	0.002	0.003	0.013	0.025	0.200
2008	0.024	0.002	0.007	0.016	0.201	0.001	0.012	0.021	0.078	0.152	0.123	0.001	0.002	0.003	0.002	0.006	0.001	0.036	0.021	0.025	0.014	0.009	0.002	0.003	0.014	0.025	0.200
2009 (2)	0.024	0.003	0.007	0.016	0.199	0.001	0.011	0.022	0.077	0.152	0.121	0.001	0.002	0.003	0.002	0.006	0.001	0.036	0.021	0.026	0.014	0.010	0.003	0.003	0.014	0.025	0.201

Appendix V

Consumers´uncertainty on Personal vs General and Past vs Future economic conditions

	Personal		General	
	(Q1) Past	(Q2) Future	(Q3) Past	(Q4) Future
AUSTRIA	0.98	2.97	2.43	4.04
BELGIUM	2.96	6.69	6.05	10.8
GERMANY	1.36	4.73	2.32	5.58
DENMARK	0.66	3.70	7.11	8.85
GREECE	0.16	4.46	1.95	7.68
SPAIN	1.09	9.68	5.37	14.8
FINLAND	0.60	3.59	3.34	4.89
FRANCE	0.48	4.23	1.66	8.76
IRELAND	0.94	4.88	1.97	6.97
ITALY	0.50	4.68	1.95	6.32
LUXEMBOURG	1.16	3.46	4.67	5.59
NETHERLANDS	1.08	4.50	7.00	11.0
SWEDEN	0.77	2.21	5.49	4.77
PORTUGAL	1.33	11.2	5.47	15.7
UK	1.57	5.93	4.62	9.84
EU11	1.02	5.08	3.93	8.58

EU11=Belgium, Germany, Denmark, Greece, Spain, Finland, France, Ireland, Italy, Netherlands, UK (sample 87:11-05:07)
Full sample average of responses "don't' know" (in % of total) to the questions:
Q1=How has the financial situation of your household changed over the last 12 months?
Q2=How do you expect the financial position of your household to change over the next 12 months?
Q3=How do you think the general economic situation in the country has changed over the past 12 months?
Q4=How do you expect the general economic situation in the country to develop over the next 12 months?

Source: EU Commission

Appendix W

European Consumer survey

Starting date of the confidence indicator by country

Member States	Starting year
European Union	January 1985
Euro area	January 1985
Belgium	January 1985
Czech Republic	January 1995
Denmark	January 1985
Germany	January 1985
Estonia	July 1992
Greece	January 1985
Spain	June 1986
France	January 1985
Ireland	January 1985
Italy	January 1985
Cyprus	May 2001
Latvia	May 2001
Lithuania	May 2001
Luxembourg	January 2002
Hungary	February 1992
Netherlands	January 1985
Austria	October 1995
Poland	May 2001
Portugal	June 1986
Slovenia	March 1996
Slovak Republic	April 1999
Finland	November 1987
Sweden	October 1995
United Kingdom	January 1985
Bulgaria	May 2001
Romania	May 2001

Source: EU Commission

Appendix X

List of EU LCCs

Country	Airline	Ownership relations with other airlines	Former names	Notes
Albania	Belle Air			
Austria	InterSky			
Austria	Niki	24% Air Berlin (2004-)		Formed from former Aero Lloyd Austria operation
Belgium	Virgin Express	51% Virgin Group (max 100%, min 51%, 1996-2007)	EuroBelgian (1990-1996)	Merged with SN Brussels Airlines under a holding company SN Airholding in 2005; Brussels Airlines was formed in 2006 and took over both SN Brussels Airlines and Virgin Express in 2007
Bulgaria	Wizz Air Bulgaria	100% Wizz Air (2005-)		
Czech Republic	Smart Wings	100% Travel Service Airlines (2004-, Travel Service has been majority owned by Icelandair Group since 2007)		
Denmark	Sterling	100% Fons Eignarhaldsfelag hf (majority owner company of Iceland Express, 2005), FL Group (parent company of Icelandair, 2005-2008), 100% Cimber (2008-)	Sterling European Airways (1994-2005)	Bankrupted and Cimber acquired 100% in 2008
Finland	Blue 1	SAS (1998-)	Air Botnia (1987-2004)	
Finland	Flying Finn			
France	Aeris		Air Toulouse (1990-1999)	
France	Flywest			
France	Virgin Express France	100% Virgin Express Holdings (1997-1998)	Air Provence Charter (1995-1997)	
Germany	Air Berlin			Merged with dba in 2007
Germany	Condor Flugdienst	24.9% Lufthansa (max 100%, min 10%, 1959-), 75.1% Thomas Cook Group (max 90%, 2001-)	Deutsche Flugdienst (1955-1961)	All the flights started to fly under Thomas Cook Banner in 2003
Germany	Dauair			
Germany	dba	40% Crossair (1978-1992), 100% British Airways (min 49%, 1992-2003), 64% owner of Germania (2005), 100% Air Berlin (2006-2007)	Delta Air Regionalflugverkehr (1978-1992), Deutsche BA (1992-2003)	Merged with Germania Express in 2005; Merged into Air Berlin in 2007
Germany	Germania Express (gexx)	100% Germania (2003-2005), 100% dba (2005)		Merged into dba in 2005
Germany	Germanwings	100% Eurowings (2002-2008), 100% Lufthansa (2009-)		
Germany	TUIFly	100% TUI AG (2002-)	Hapag-Lloyd Express (HLX, 2002-2007)	Integrated with Hapagfly to become TUIFly in 2007 (Hapag-Lloyd Express became a marketing brand)
Hungary	SkyEurope Hungary	100% SkyEurope Airlines (2003-)		
Hungary	Wizz Air			
Iceland	Iceland Express			
Ireland	Aer Arann			
Ireland	Eujet			
Ireland	JetMagic			
Ireland	Ryanair			Merged with Buzz in 2003
Ireland	Virgin Express (Ireland)	100% Virgin Express Holdings (1998-2001)		
Italy	Air Europe	27.5% Eurofly (1991-1998), 49.9% SAir Group (1998-2002), 100% Alitalia (2006-)		Merged with Volare Airlines in 2000 (became one brand of Volare)
Italy	Air Service Plus			Currently operated by Axis Airlines
Italy	Blu-Express	100% Blue Panorama Airlines (2005-)		
Italy	Ciao Fly			
Italy	ItAli Airlines			
Italy	Meridiana		Alisarda (1963-1991)	
Italy	Myair (My Way Airlines)			
Italy	Volare Airlines (volareweb.com)	49.9% SAir Group (min 34%, 1998-2002), 100% Alitalia (2006-)		Merged with Air Europe in 2000; Ceased operations in 2004; Resumed operations in 2005

(table continues on next page)

Appendix X (Continued)

List of EU LCCs

Country	Airline	Ownership relations with other airlines	Former names	Notes
Italy	Wind Jet			
Malta	Britishjet			Licensed by UK CAA
Malta	Fare4U	a division of Air Malta (2004-2006)		Integrated into Air Malta in 2006
Netherlands	Basiq Air	100% Transavia (owned 100% by KLM and then Air France-KLM, 2000-2005)		Merged into Transavia in 2005
Netherlands	Dutchbird			
Netherlands	Transavia.com	100% KLM (min 40%, 1988-2004), 100% Air France-KLM (2004-)	Transavia Limburg (1965-1966), Transavia Holland (1966-1986), Transavia Airlines (1986-2005)	Merged with Basiq Air and re-branded as Transavia.com in 2005
Netherlands	V Bird			
Norway	Color Air			
Norway	Norwegian Air Shuttle	5% Finnair (2007-)		Formed in 1993 following collapse of Busy Bee Airlines
Poland	Air Polonia			
Poland	Centralwings	100% LOT Polish Airlines (2004-)		Became a charter-only operation in 2008
Portugal	Hi Fly		Air Luxor (1988-2005)	Concentrated on charter operations as a result of sale of scheduled operations to Longstock Financial Group in 2006
Romania	Blue Air			
Russian Federation	SkyExpress	80% KrasAir-related investors		
Slovak Republic	SkyEurope Airlines			SkyEurope Holding AG was established in Vienna in 2005
Spain	Clickair	20% Iberia (voting 80%, 2006-2009)		Merged into Vueling in 2009
Spain	Vueling	3.7% JetBlue Airways' investors (max 7%, 2004-2009), 45% Iberia (2009-), 5% Nefinsa (parent company of Air Nostrum, 5%, 2009-)		Merged with Clickair in 2009
Sweden	FlyMe			
Sweden	Flynordic	100% Finnair (min 85%, 2003-), 100% Norwegian Air Shuttle (2007-2008)	Nordic Airlink (2000-2004)	Integrated into Norwegian Air Shuttle in 2008
Sweden	Snalskjutsen	a division of Malmo Aviation (2002-2005)		Integrated into Malmo Aviation in 2005
Sweden	Snowflake	a division of SAS (2002-2004)		Integrated into SAS in 2005
Sweden	Sverigeflyg			Comprises of Blekingeflyg, Gotlandsflyg, Kalmarflyg, Kullaflyg and Sundsvallsflyg
Switzerland	easyJet Switzerland	100% Trans European Airways (1988-1991), 49% easyJet (min	TEA Basel (1988-1998)	

(table continues on next page)

Appendix X (Continued)

List of EU LCCs

Country	Airline	Ownership relations with other airlines	Former names	Notes
Switzerland	Flybaboo			
Switzerland	Helvetic Airways		Odette Airways (2001-2003)	
Turkey	Atlasjet Airlines			
Turkey	Corendon Airlines			
Turkey	Onur Air			
Turkey	Pegasus Airlines	a controlling stake by Aer Lingus (1989-1994)		
Turkey	SunExpress	50% THY Turkish Airlines (1990-), 50% Lufthansa (1990-1995, 2007-), 50% Condor (1995-2007)		
United Kingdom	AB Airlines		Air Bristol (1992-1995)	Formed in 1992 by a group of former Brymon Airlines
United Kingdom	Air Scotland			Formed in 2002 for Electra Airlines (Greece); Switched agreement to Air Holland in 2003; Ceased agreement with Air Holland and formed Greece Airways in 2004
United Kingdom	Air Southwest			
United Kingdom	BMIBaby	100% Airlines of Britain Group (parent company of BMI British Midland, 2002-)		
United Kingdom	Buzz	100% KLM UK (1999-2003), Ryanair (2003)		Merged into Ryanair in 2003
United Kingdom	Debonair			
United Kingdom	easyJet	16.9% FL Group (then parent company of Icelandair, min 8.4%, 2005-2006)		
United Kingdom	Flybe	15% British Airways (2007-)	Jersey European Airways (1979-2000), British European Airways (2000-2002)	Merged with Spacegrand Aviation in 1985, Merged with BA Connect in 2007
United Kingdom	FlyGlobespan			
United Kingdom	GO	100% British Airways (1997-2001), 100% easyJet (2002)		Merged into easyJet in 2002
United Kingdom	Jet Green			
United Kingdom	Jet2.com	a division of Channel Express (2002-2006)		Channel Express was rebranded and replaced by Jet2.com in 2006
United Kingdom	Manx2			
United Kingdom	Monarch Scheduled	a division of Monarch Airlines (2004-)		
United Kingdom	Mytravellite	100% Mytravel Airways (2002-2005)		Integrated into Mytravel Airways in 2003
United Kingdom	Now Airlines			Never started
United Kingdom	Thomson Airways	100% TUI AG (2004-2007), TUI Travel Plc (2007-)	Thomsonfly (2004-2008)	Merged with Britannia Airways in 2005, Merged with First Choice Airways to form Thomson Airlines in 2008
United Kingdom	XL Airways	100% Sky Airlines Cyprus (Libra Group, min 33%, 2000-2004), 100% Air Atlanta Icelandic (Avion Group, min 40.5%, 2004-2006)	Sabre Airways (1994-2002), Excel Airways (2002-2006)	

Source ICAO, 2009 Tenth Session of the Statistics Division WP9: Definition and identification of Low Cost Carriers
http://legacy.icao.int/STA10/Documentation.htm

Appendix Y

List of ERAA and AEA airlines

Table Y1: ERAA airlines

Adria Airways	Aegean Airlines
Aer Arann	Aeroflot-Nord
Air Alps Aviation	Air Iceland
Air Nostrum	Air Southwest
Air Urga	Air Baltic
Airlinair	Alitalia Express
Astra Airlines	Atlantic Airways
Augsburg Airways	Aurigny AirServices
Avanti Air	Avitrans Nordic
Baboo	Belle Air
Binter Canarias	Blue Islands
Blue1	Brit Air
Carpatair	Cimber Air
City Airline	CityJet
Contact Air	DanishAirTransport
Darwin Airline	Denim Air
DOT LT	Eastern Airways
Epsilon Aviation	EuroLOT
Eurowings	Finncomm Airlines
Golden Air	Isles of Scilly Skybus
Jet Air	KLM cityhopper
Lufthansa CityLine	Luxair
Malmö Aviation	Macedonian Airlines
Montenegro Airlines	OLT
Palestinian Airlines	Pantheon Airlines
PGA - Portugalia Airlines	Régional
SATA Air Açores	Skyways Express
Titan Airways	Trade Air
Tyrolean Airways)	VLM Airlines
Volare SpA)	Welcome Air
West Air Sweden	Widerøe's

Appendix Y (Continued)

List of ERAA and AEA airlines (continued)

Table Y2: AEA airlines

Members of the AEA	
AF Air France(1)	France
AP Air One	Italy
AY Finnair	Finland
AZ Alitalia	Italy
BA British Airways (2)	Great Britain
BD bmi	Great Britain
CV Cargolux	Luxembourg (all-cargo carrier)
CY Cyprus Airways	Cyprus
EI Aer Lingus	Ireland (no data from 2002 onwards)
FI Icelandair	Iceland
IB Iberia	Spain
IG Meridiana	Italy (no longer a member since 2004)
JK Spanair	Spain
JP Adria Airways	Slovenia
JU JAT Airways	Serbia and Montenegro
KL KLM	Netherlands
KM Air Malta	Malta
LG Luxair	Luxembourg
LH Lufthansa (3)	Germany
LO LOT Polish Airlines	Poland
LX Swiss International Airlines	Switzerland
LZ Balkan	Bulgaria (bankrupt: no data from 2000)
MA Malev	Hungary
OA Olympic Airlines	Greece
OK Czech Airlines	Czech Republic
OS Austrian (4)	Austria
OU Croatia Airlines	Croatia
PS Ukraine International Airlines	Ukraine (member since Jan 2008 / reports data from Jan 2007)
RO Tarom	Romania
SK SAS Scandinavian Airlines	Norway, Sweden, Denmark
SN Brussels Airlines	Belgium (reporting from January 2002 / removed SN from name / merged with Virgin Express in March 2007)
XSN Sabena	Belgium (ceased operations 7th November 2001)
SR Swissair	Switzerland (ceased operations end March 2002)
TK Turkish Airlines	Turkey
TP TAP Air Portugal	Portugal
VS Virgin Atlantic Airways	Great Britain (member since 01-Jul-2003 - reporting from Jan-2002 data)
VV AeroSvit	Ukraine (member since Jan 2008 / reports data from Jan 2007)

Appendix Z

EU market: Tests and specifications for Model 1 of Log (RPK 85-2010)

Table Z1: Normality test of Log RPK 85-2010

Tests for Normality

Test	Statistic		p Value	
Shapiro-Wilk	W	0.959265	Pr < W	0.3773
Kolmogorov-Smirnov	D	0.099872	Pr > D	>0.1500
Cramer-von Mises	W-Sq	0.03623	Pr > W-Sq	>0.2500
Anderson-Darling	A-Sq	0.287259	Pr > A-Sq	>0.2500

Table Z2: Model 1 specifications for Log RPK 85-2010

Model 1 Variable: Log Total RPK85-2010	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-6.76676	4.66634	-1.45	0.1605
LnRealGDP	1	1.50006	0.4338	3.46	0.0021
LNReal Yields	1	-0.53864	0.23333	-2.31	0.0303

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	2	4.59701	2.2985	416.36	<.0001
Error	23	0.12697	0.00552		
Corrected Total	25	4.72398			
Root MSE	0.0743	R-Square	0.9731		
Dependent Mean	5.67663	Adj R-Sq	0.9708		
Coeff Var	1.30888				

Appendix AB

EU market: Tests and specifications for Model 1 and 2 of Log (RPK 85-2007)

Table AB1: Model 1 specifications for Log RPK 85-2007

Model 1 Variable: Log Total RPK85-2007	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-7.39659	3.22357	-2.29	0.0327
LnRealGDP	1	1.53524	0.29979	5.12	<.0001
LNReal Yields	1	-0.43701	0.16128	-2.71	0.0135
		Analysis of Variance			
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	3.25186	1.62593	662.33	<.0001
Error	20	0.0491	0.00245		
Corrected Total	22	3.30096			
Root MSE	0.04955	R-Square	0.9851		
Dependent Mean	5.59224	**Adj R-Sq**	**0.9836**		
Coeff Var	0.88599				

Table AB2: Model 2 specifications for Log RPK 85-2007

Model 2 Variable: Log RPK 85-2007	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-3.85091	2.72202	-1.41	0.1733
LnRealGDP	1	0.96874	0.28314	3.42	0.0029
LnCCI2007	1	0.54998	0.15143	3.63	0.0018
LNReal Yields	1	-0.70994	0.14768	-4.81	0.0001
		Analysis of Variance			
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	3	3.27198	1.09066	715.08	<.0001
Error	19	0.02898	0.00153		
Corrected Total	22	3.30096			
Root MSE	0.03905	R-Square	0.9912		
Dependent Mean	5.59224	**Adj R-Sq**	**0.9898**		
Coeff Var	0.69836				

Appendix AC

EU market: Significance tests for Model 1 and 2 of Log (RPK 85-2007)

Table AC1: Correlation matrix of the regressors for Log RPK 85-2007

Model 1: Correlation of Estimates			Variance
Variable: Log RPK 85-2007	LnRealGDP	LNReal Yields	Inflation
Intercept	-0.9995	-0.9828	0
LnRealGDP	1.0000	0.9768	21.8316
LNReal Yields	0.9768	1.0000	21.8316

Model 2: Correlation of Estimates					
Variable	Intercept	LnRealGDP	LnCCI	LNReal Yields	Variance Inflation
Intercept	1.0000	-0.9763	0.3587	-0.9723	0
LnRealGDP	-0.9763	1.0000	-0.5509	0.9821	31.34413
LnCCI	0.3587	-0.5509	1.0000	-0.5089	1.49859
LNReal Yields	-0.9723	0.9821	-0.5089	1.0000	29.46043

Table AC2: Specifications of Model 1bis and Model 1ter for Log (RPK 85-2007)

Model 1bis

Variable Log RPK 85-95	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-9.71751	3.91288	-2.48	0.0274
LNReal Yields	1	-0.64651	0.14169	-4.56	0.0005
LnRealGDP	1	1.6709	0.34444	4.85	0.0003

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	2	1.15375	0.57688	378.88	<.0001
Error	11	0.01979	0.00152		
Corrected Total	13	1.17355			
Root MSE	0.039	R-Square	0.9831		
Dependent Mean	5.3997	**Adj R-Sq**	**0.9805**		
Coeff Var	0.7227				

Model 1ter

Variable Log RPK 95-07	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-7.3519	3.5517	-2.07	0.0653
LNReal Yields	1	-0.44515	0.16023	-2.78	0.0195
LnRealGDP	1	1.53328	0.33785	4.54	0.0011

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	2	0.57421	0.2871	135.89	<.0001
Error	13	0.02113	0.00211		
Corrected Total	15	0.59533			
Root MSE	0.046	R-Square	0.9645		
Dependent Mean	5.8758	**Adj R-Sq**	**0.9574**		
Coeff Var	0.7823				

Appendix AD

EU market: Comparison of Models 1, 2 and 3 of Log (RPK 85-2007)

Table AD1: Comparison of significance tests for Model 1 and 2 of Log (RPK 85-2007)

Number in Model 1	Adjusted R-Square	C(p)	RMSE	SBC	SSE	Variables in Model
2	0.9836	5.3467	0.0495	-132.03	0.049	LnRealGDP LnReal Yields
Number in Model 2	**Adjusted R-Square**	**C(p)**	**RMSE**	**SBC**	**SSE**	**Variables in Model**
3	0.9898	3.0411	0.0390	-141.02	0.029	LnRealGDP LnReal Yields LnCCI

Table AD2: Model 3 of Log RPK 85-2007

Model 3 Variable: Log RPK 85-2007	Label	DF	Parameter Estimate	Standard Error	t Value
Intercept	Intercept	1	-16.08919	0.54599	-29.47
LnRealGDP		1	2.34148	0.05895	39.72
Dummy		1	-0.11917	0.03368	-3.54

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	2	3.25968	1.62984	789.57	<.0001
Error	20	0.04128	0.00206		
Corrected Total	22	3.30096			
Root MSE	0.04543	R-Square	0.9875		
Dependent Mean	5.59224	Adj R-Sq	0.9862		
Coeff Var	0.81244				

Table AD3: Statistical tests for Model 3 of Log RPK 85-2007

Number in Model 3	Adjusted R-Square	C(p)	RMSE	SBC	SSE	Variables in Model
2	0.9862	12.7531	0.04543	-136.01734	0.04128	LnRealGDP Dummy

Appendix AE

EU market: Comparison with Model 3 of Log (RPK 85-2000)

Table AE1: Model 1 specifications for Log RPK 85-2000

Model 1 Variable: Log RPK 85-2000	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-18.1378	0.99285	-18.27	<.0001
LNGDPR$2000	1	2.61568	0.11033	23.71	<.0001
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	1.14503	1.14503	562.09	<.0001
Error	14	0.02852	0.00204		
Corrected Total	15	1.17355			
Root MSE	0.04513	R-Square	0.9757		
Dependent Mean	5.39965	**Adj R-Sq**	**0.974**		
Coeff Var	0.83587				

Table AE2: Model 1 bis specifications for Log RPK 85-2000

Model 1 bis Variable: Log RPK 85-2000	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-9.71751	3.91288	-2.48	0.0274
LNReal Yields	1	-0.64651	0.14169	-4.56	0.0005
LNReal GDP Per Capita	1	1.6709	0.34444	4.85	0.0003
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	1.15375	0.57688	378.88	<.0001
Error	13	0.01979	0.00152		
Corrected Total	15	1.17355			
Root MSE	0.03902	R-Square	0.9831		
Dependent Mean	5.39965	**Adj R-Sq**	**0.9805**		
Coeff Var	0.72265				

Appendix AF

EU market: Model 1 and 2 of Log (RPK 95-2007) for EU network carriers

Table AF1: Specifications of Model 1 and 2 for the Network segment between 1995 and 2007

Model 1 Variable: Log RPK Network 95-07	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-6.71531	4.00361	-1.68	0.1244
LnRYields Network	1	-0.51043	0.17627	-2.9	0.016
LnReal GDP Per Capita95	1	1.27703	0.34375	3.71	0.004
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.32229	0.16114	135.9	<.0001
Error	10	0.01186	0.00119		
Corrected Total	12	0.33415			
Root MSE	0.03444	R-Square	0.9645	.	.
Dependent Mean	5.11589	**Adj R-Sq**	**0.9574**	.	.
Coeff Var	0.6731			.	.

Model 2 Variable: Log RPK Network 95-07	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-3.10048	3.17911	-0.98	0.3549
LnRYields Network	1	-0.76819	0.15482	-4.96	0.0008
LnCCI2007	1	0.51573	0.16829	3.06	0.0135
LnReal GDP Per Capita95	1	0.77015	0.30267	2.54	0.0315
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	3	0.32834	0.10945	169.76	<.0001
Error	9	0.0058	0.000645		
Corrected Total	12	0.33415			
Root MSE	0.02539	R-Square	0.9826		
Dependent Mean	5.11589	**Adj R-Sq**	**0.9768**		
Coeff Var	0.49633				

Appendix AG

EU market: Model 1 and 2 of Log (RPK 95-2007) for EU charter carriers

Table AG1: Specifications of Model 1 and 2 for the Charter segment between 1995 and 2007

Model 1 Variable: Log RPK Charter 95-07	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-0.93082	1.11372	-0.84	0.4211
LnRealGDP95-07	1	0.62073	0.11868	5.23	0.0003
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	1	0.03798	0.03798	27.36	0.0003
Error	11	0.01527	0.00139		
Corrected Total	12	0.05324			
Root MSE	0.03726	R-Square	0.7132	.	.
Dependent Mean	4.8942	**Adj R-Sq**	**0.6872**	.	.
Coeff Var	0.76125			.	.

Model 2 Variable: Log RPK Charter 95-07	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-2.79274	1.08055	-2.58	0.0272
LnRealGDP95-07	1	0.59704	0.0925	6.45	<.0001
LnCCI2007	1	0.46072	0.16038	2.87	0.0166
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.04488	0.02244	26.82	<.0001
Error	10	0.00837	0.000837		
Corrected Total	12	0.05324			
Root MSE	0.02892	R-Square	0.8429		
Dependent Mean	4.8942	**Adj R-Sq**	**0.8115**		
Coeff Var	0.59097				

Appendix AH

Model 1 and 2 of Log (RPK 95-2007) for the whole European traffic

Table AH1: Specifications of Model 1 and 2 for the whole European traffic between 1995 and 2007

Model 1 Variable: LogRPKGlobal 95-07	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-7.3519	3.5517	-2.07	0.0653
LnReal Yields 95-07	1	-0.44515	0.16023	-2.78	0.0195
LnRealGDP95-07	1	1.53328	0.33785	4.54	0.0011
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.57421	0.2871	135.89	<.0001
Error	10	0.02113	0.00211		
Corrected Total	12	0.59533			
Root MSE	0.04596	R-Square	0.9645		
Dependent Mean	5.87575	**Adj R-Sq**	**0.9574**		
Coeff Var	0.78227				

Model 2 Variable: LogRPKGlobal 95-07	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-4.5905	3.20544	-1.43	0.1859
LnReal Yields	1	-0.70753	0.17608	-4.02	0.003
LnRealGDP95-07	1	1.00159	0.36526	2.74	0.0228
LnCCI2007	1	0.64378	0.28008	2.3	0.0471
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	3	0.58202	0.19401	131.16	<.0001
Error	9	0.01331	0.00148		
Corrected Total	12	0.59533			
Root MSE	0.03846	R-Square	0.9776		
Dependent Mean	5.87575	**Adj R-Sq**	**0.9702**		
Coeff Var	0.65455				

Appendix AI

Model 1 of Log (RPK 85-2010) for the EU-US traffic

Table AI1: Specifications of Model 1 for Log RPK 1985-2010

Model1 Variable: Log RPK 1985-2010	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Heteroscedasticity Consistent Standard Error	t Value	Pr > |t|
Intercept	1	-4.86907	1.58166	-3.08	0.0082	1.03116	-4.72	0.0003
LRINCAGG	1	1.03419	0.1532	6.75	<.0001	0.09914	10.43	<.0001

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	0.2172	0.2172	45.57	<.0001
Error	14	0.06673	0.00477		
Corrected Total	15	0.28393			
Root MSE	0.06904	R-Square	0.765		
Dependent Mean	5.80728	**Adj R-Sq**	**0.7482**		
Coeff Var	1.18884				

Appendix AJ

Comparison of Model 1 and 2 of Log (RPK 85-2007) for the EU-US traffic

Table AJ1: Specifications for Model 1 and 2 for Log RPK 85-2007

Model 1 Variable: Log RPK 85-2007	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1	-8.57838	2.88927	-2.97	0.0128
LNReal EU GDP Per Capita PPP	1	1.39931	0.28177	4.97	0.0004

Analysis of Variance

Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**	
Model	1	0.12928	0.12928	24.66	0.0004	.
Error	11	0.05766	0.00524			.
Corrected Total	12	0.18695				.
Root MSE	0.0724	R-Square	0.6916	.	.	.
Dependent Mean	5.76998	**Adj R-Sq**	**0.6635**	**.**	.	.
Coeff Var	1.2548			.	.	.

Model 2 Variable: Log RPK 85-2007	**Label**	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	Intercept	1	-16.8924	1.57701	-10.71	<.0001
LNReal EU GDP Per Capita PPP	LNReal GDP Per Capita PPP	1	1.60779	0.115	13.93	<.0001
LnCCIAgg		1	1.34351	0.17433	7.71	<.0001

Analysis of Variance

Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	2	0.17864	0.08932	107.5	<.0001
Error	10	0.00831	0.000830		
Corrected Total	12	0.18695			
Root MSE	0.02883	R-Square	0.9556		
Dependent Mean	5.76998	**Adj R-Sq**	**0.9467**		
Coeff Var	0.49958				

Appendix AK

Model 1 and 2 of Log (RPK 85-2000) for EU-US traffic

Table AK1: Specifications of Model 1 for Log RPK 1985-2000

Variable	Label	DF	Model 1 Parameter Estimate	Log RPK 85-00 Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	Intercept	1.00	-11.52	0.73	-15.69	<.0001	0.00
LNRYIELDAEA 2000		1.00	-0.42	0.04	-9.88	0.00	7.70
LRGDP AGG2000		1.00	1.99	0.07	27.49	<.0001	7.70

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	2.00	0.82	0.41	5,238.95	<.0001
Error	4.00	0.00	0.00		
Corrected Total	6.00	0.82			
Root MSE	0.01	R-Square	1.00		
Dependent Mean	5.58	**Adj R-Sq**	**1.00**		
Coeff Var	0.16				

Variable	Label	DF	Model 2 Parameter Estimate	LogRPK 85-00 Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	Intercept	1	-28.39484	1.97582	-14.37	0.0007	0
LRINCAGG00		1	3.33969	0.19275	17.33	0.0004	20.88058
LnExchaRate		1	-0.3422	0.08032	-4.26	0.0237	20.88058

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F	
Model	2	0.0959	0.04795	1819.71	<.0001	.
Error	3	7.91E-05	0.00002635			.
Corrected Total	5	0.09597				.
Root MSE	0.00513	R-Square	0.9992	.	.	.
Dependent Mean	5.7128	**Adj R-Sq**	**0.9986**	.	.	.
Coeff Var	0.08985			.	.	.

Appendix AL

Model 1 and 2 of Log (RPK 2000-2010) for the whole EU-US traffic

Table AL1: Model 1 and 2 specifications for Log RPK 2000-2010

Model 1 Variable: Log RPK 2000-2010	**Label**	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	Intercept	1	-4.6851	3.18656	-1.47	0.1756
LRINCAGG		1	1.01601	0.30679	3.31	0.0091
			Analysis of Variance			.
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**	.
Model	1	0.05703	0.05703	10.97	0.0091	.
Error	9	0.0468	0.0052			.
Corrected Total	10	0.10383				.
Root MSE	0.07211	R-Square	0.5493	.	.	.
Dependent Mean	5.86772	**Adj R-Sq**	**0.4992**	.	.	.
Coeff Var	1.22895			.	.	.
Model 2 Variable: Log RPK 2000-2010	**Label**	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	Intercept	1	-11.3649	2.79515	-4.07	0.0036
LnCCIAgg		1	1.00455	0.27927	3.6	0.007
LRINCAGG		1	1.22141	0.20908	5.84	0.0004
			Analysis of Variance			.
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**	.
Model	2	0.08595	0.04298	19.23	0.0009	.
Error	8	0.01788	0.00224			.
Corrected Total	10	0.10383				.
Root MSE	0.04728	R-Square	0.8278	.	.	.
Dependent Mean	5.86772	**Adj R-Sq**	**0.7847**	.	.	.
Coeff Var	0.80571			.	.	.

Appendix AM

Freedoms of the air

Table AM1: List of the nine traffic rights

1)The right or privilege, in respect of scheduled international air services, granted by one State to another State or States to fly across its territory without landing 2) The right or privilege, in respect of scheduled international air services, granted by one State to another State or States to land in its territory for non-traffic purposes. 3) The right or privilege, in respect of scheduled international air services, granted by one State to another State to put down, in the territory of the first State, traffic coming from the home State of the carrier 4) The right or privilege, in respect of scheduled international air services, granted by one State to another State to take on, in the territory of the first State, traffic destined for the home State of the carrier 5) The right or privilege, in respect of scheduled international air services, granted by one State to another State to put down and to take on, in the territory of the first State, traffic coming from or destined to a third State 6) The right or privilege, in respect of scheduled international air services, of transporting, via the home State of the carrier, traffic moving between two other States 7) The right or privilege, in respect of scheduled international air services, granted by one State to another State, of transporting traffic between the territory of the granting State and any third State with no requirement to include on such operation any point in the territory of the recipient State, i.e the service need not connect to or be an extension of any service to/from the home State of the carrier. 8) The right or privilege, in respect of scheduled international air services, of transporting cabotage traffic between two points in the territory of the granting State on a service which originates or terminates in the home country of the foreign carrier or (in connection with the so-called Seventh Freedom of the Air) outside the territory of the granting State (referred to as Consecutive Cabotage). 9) The right or privilege of transporting cabotage traffic of the granting State on a service performed entirely within the territory of the granting State (referred to as Stand Alone Cabotage).